THE CAUSES AND EFFECTS OF VARIATIONS IN WELFARE GENEROSITY: EXAMINING THE SOCIAL SAFETY NET

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ABSTRACT

Katherine Sacks: The Causes and Effects of Variations in Welfare Generosity:
Examining the Social Safety Net Following Devolution
(Under the direction of Daniel Gitterman)

In the first paper of this dissertation, I lay out in a uniform, quantifiable manner a framework for examining the regulations and policies surrounding social safety net programs. By creating a database of laws and procedures surrounding SNAP, TANF, and Medicaid, it is then possible to examine and compare those rules using quantitative methods. In the second paper, I do this by aggregating in two different ways the rules in the database that were generated in the first paper: by averaging them into an index and by using factor analysis. Although the factor analysis models are a poor fit, an examination of the averaged scores for each state over the period shows that generosity is increasing in almost every state over time. In the third paper, I use the index from the second paper as an explanatory variable in a mixed-effects model to examine maternal mortality in the United States from 2005 to 2012. By using the index as an independent variable, I meant to uncover the effects of safety net generosity on maternal mortality in each state for each year. The results of this analysis show that, although the three individual programs do not demonstrate an effect of maternal mortality on their own, the combination of the three programs into a safety net or a package of programs does improve mortality. Although this is true for the entire population and for White women, Black maternal mortality does not reflect the population-wide results, indicating that more specific analysis by race is warranted in the future.

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INTRODUCTION

The purpose of this dissertation was to develop a conceptual framework and metrics on the generosity of social assistance in each state. In the third paper of this dissertation, I hope to evaluate the impact of that assistance climate on a specific public health outcome, severe maternal morbidity. The rules and regulations passed by states with respect to federally financed, means-tested, social safety net programs provide an ideal opportunity for comparative analysis. The programs selected for analysis are the Supplemental Nutrition Assistance Program (SNAP), Temporary Assistance for Needy Families (TANF) and Medicaid. These three means-tested federal programs vary in generosity across states.

One major contribution of this dissertation is that in it I created an aggregate measure of social safety net generosity and applied that measure to population health outcomes. The purpose of creating this database of rules was ultimately to generate a measure of generosity that would serve as an explanatory variable in quantitative statistical models. Public health scholars certainly acknowledge the influence of federal and state government policies on individual and population health, but the researchers who have examined these effects have rarely instrumentalized this input in a sophisticated way. Too often, public health analysts have relied on reductive measures of government policy (e.g., fiscal expenditures, date of implementation or number of people affected). The problem with these measures is that they have failed to account for small variation in policy regulations across states. Implementation and population numbers are simple black-and-white instruments that are used to determine whether a policy affects someone or whether it does not, while expenditures cannot distinguish where and how public monies are spent. This means that high levels of direct cash assistance can look identical to meager cash assistance coupled with high administrative costs.

Therefore, I have aimed to bridge that divide between sophisticated methodologies that look at policies, but not outcomes, and the more basic attempts to understand policy effects on public health, using crude measures of those policies. The construction of a generosity index (or generosity scale) to measure the provision of the social safety net builds on the traditions of policy analysis and political science. However, the application of that measure, to answer questions about the effects of the social safety net on population health outcomes, represents a development in the area of more traditional public health analyses of population health.

In the first paper of the dissertation, I aggregate the rules governing these programs in each state into a policy database that scores each rule numerically. The resulting database of rules and regulations that govern these programs is used for a variety of analyses. In the second paper, I aggregate the database of rules into a single measure of generosity. First, I create a rough generosity index by averaging together the numerical scores in the database. I use a more advanced statistical technique to transform the database into a generosity scale. Confirmatory factor analysis is performed on three hypothesized models of how underlying generosity might manifest in program regulations. Finally, in the third paper, I select a measure of generosity (from among those created) to be used as an explanatory variable in the analysis of adverse maternal birth outcomes.

The goal is to show that state social safety can determine population health outcomes. Although administrative or regulatory changes to programs can seem technical rather than impactful, they represent more than bureaucratic red tape. The rules and regulations governing the provision of the social safety net affect can have real consequences on public health, and research into these effects is necessary if stakeholders aim to make good social and health policy.

PAPER 1: ASSESSING GENEROSITY IN STATE POLICIES:[1] THE SOCIAL SAFETY NET AS AN UNDERLYING DETERMINANT OF THE PUBLIC'S HEALTH

Section 1.1 Generosity and the Social Safety Net

To date, scholars in the fields of public policy, public administration, and political science that take advantage of more sophisticated methodologies have tended to present policies and regulations as an output, rather than as an input. Techniques such as principle components analysis or cluster analysis have been extended from their social science origins in sociology, education, and psychometrics to the fields of public policy or political science, but this is generally as far as the extension goes. These analytic techniques and their results are the products of such studies, but rarely do authors go beyond that analysis to use these products in other ways.

In this paper, I examine variations in the generosity of three major federal social safety net programs—income support (TANF), food assistance (SNAP), and health care (Medicaid)—combining the eligibility for and the value of these safety net benefits into a combined generosity score for each state. In Section 1.2, I provide a methodological justification for carrying out the aggregation of various state rules; In Section 1.3, I describe the methods and procedures used to quantify welfare generosity in state law from 2000 to 2016, coding laws across key social assistance programs in all 50 states and Washington, D.C., according to their eligibility criteria, benefit levels, and program administration. Situating this study in the broader framework of social determinants of health, in Section 1.4, I describe the role of social policy in influencing

[1] Much of this paper comes from an unpublished manuscript coauthored with Ben Meier, Yuna Kim, and Ashley Fox; the coding builds on work done with Wenhui Feng and Cesar Renteria.

population health, providing a basis to assess the impact of law on the public's health. In Section 1.5, I describe the limitations of the current analysis and the possible future applications for the process before I ultimately conclude that coding state laws provides a path to assess empirically the impact of social safety net rules on population health in the Unites States.

To give substance to the concept of "Health in all Policies," evidence of the impact of social policies on health outcomes is critical. I hypothesized that higher state welfare generosity across states and changes in generosity over time would be associated with public health indicators (especially the infant health indicators that are most sensitive to economic inequality). Controlling for state sociodemographic characteristics (e.g., empirical assessment of state welfare generosity) can contribute to understanding of the legal factors that give rise to vast health inequalities across the American states. State welfare programs have faced a series of retrenchments since the 1990s[2]; therefore, evidence to support the public health benefits of state welfare law could support renewed attention to safety net programs and social welfare spending.

It is necessary to measure facets of state laws to assess social welfare generosity. With many social policy decisions delegated to the states, the United States is often referred to as a collection of numerous semiautonomous social safety nets, rather than as a single, federal welfare state. This is the danger of living in a federal system in which decisions about social policy are devolved from the national level: What one gets depends on where one lives (Michener, 2018). Policy determinants of health are not uniform for all Americans when even decisions about federal assistance programs are delegated to states; divergences in these programs are seen most principally in state rules regarding TANF, SNAP, and Medicaid.

[2] One of the largest retrenchments occurred in the 1996 when the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) eliminated the entitlement to cash assistance, required recipients of cash assistance to meet new work requirements, and instituted lifetime time limits on participation in the welfare program.

Section 1.2 Methodological Justification

Given the myriad rules governing program eligibility and social benefits, these laws obscure researchers' abilities to assess the comparative generosity of states social welfare systems. Although the authors of legal epidemiology studies have begun to compare individual policy and program variation across states, no previous researcher has comprehensively examined the range of programs that collectively determine welfare generosity. Through the development of a composite "generosity scale," it is possible to assess the combined generosity of a state social welfare system: "Measurement instruments that are collections of items combined into a composite score and intended to reveal levels of theoretical variables [that are] not readily observable by direct means are often referred to as *scales*" (DeVellis, 2012, p. 11). Using the resulting scores as indicators of underlying generosity, I was able to analyze this scale measure in combination with state public health outcomes, providing a basis to assert that there is a legal foundation for variations in health status across states in that legal and regulatory decisions surrounding public assistance programs serve as an accurate proxy for generosity.

The aggregation of a large number of programs or program rules into a single analysis is not a novel idea. The U.S. Department of Agriculture (USDA) has created its own SNAP Policy Index to measure the relative generosity of SNAP policies by state from year to year (USDA, Economic Research Service [ERS], n.d.; Stacy, Tiehen, & Marquardt, 2018). However, the SNAP index can only illuminate what is happening in one program, whereas the assistance actually rendered to the public depends on many programs. In this way, it makes sense to think of a "package" of policies that constitute the safety net and provide support in concert with one another. Meyers, Gornick and Peck (2001) recognized this in conceiving of a "package of support" designed to assist low-income families; their package was made up of 10 different programs and policies, all of which provided some type of assistance to families in need.

The analysis that I present likewise creates an index from more than one welfare program because assistance for those in need does not come from only a single source. Furthermore, it is of limited use to look only at the effects of a single program or policy. "Social policies at the state-level can be thought of as a portfolio of programs" (Meyers et al., 2001, p. 459); therefore, any attempt to determine how social assistance differs across jurisdictions must take into account the array of assistance programs. It is possible that states can increase generosity in one area, while simultaneously decreasing it in another. Failure to account for both of these changes would miss important information.

Section 1.3 Creating the Database of Social Safety Net Rules

Three different federal programs are included in the package of policies that I used to construct the generosity measure; all of these programs are means-tested, meaning that they target low-income households. They are all funded in full or in part by the federal government, but the administration of the programs, provision of the benefits, and many decisions about program policy are devolved to the state, and even to county or local authorities in some instances. One of the consequences of a federal system is variation across subentitites, for better or for worse. Although the programs included in the scale are authorized under federal legislation, administrative practices, provision of services, and even the eligibility requirements and benefits provided can vary wildly by jurisdiction, leading to very different experiences for similarly situated people who reside in different states, signifying a lack of "horizontal equity" (David, Smeeding, & National Bureau of Economic Research, 1985; Michener, 2018).

Although all three of the programs chosen for inclusion are federal programs, they are largely administered at a state level or under state supervision, and they vary accordingly. Beyond the federal floor required of each state, information about variation in income eligibility thresholds, I gathered categorical eligibility requirements, enrollment or reenrollment rules, conditional requirements, time limits, program-specific considerations, and benefit amounts.

TANF is the program that is known as “welfare” in the American context. It was reformed in 1996 from the former Aid to Families with Dependent Children (AFDC) with the passage of the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA), at which point it became a block grant program with greater control delegated to states. The program provides low-income families with cash assistance and certain in-kind or subsidized services such as childcare (Weaver, 2002, 2014). Data on the TANF program comes from the Urban Institute’s (n.d.) Welfare Rules Database, a comprehensive collection of rules and policies compiled annually from each state’s policy manual. Data are available from 1998 through 2016 for all 50 states and Washington, D.C. (Urban Institute, n.d.).

SNAP, formerly known as the food stamp program, provides poor individuals with money redeemable for qualifying food products at participating retailers. The least variable of all three programs, traditional SNAP eligibility requirements are generally decided at the federal level; however, states have some flexibility in program administration and have the option to confer eligibility on those receiving certain other social services (Aussenberg, 2018; Aussenberg & Falk, 2019; USDA, Food and Nutrition Service [FNS], 2018;). SNAP is a program run by the FNS within the USDA, and data regarding state policies were obtained directly from the department’s own database (USDA, ERS, n.d.).

Medicaid is government-subsidized healthcare for low-income individuals. Although means-tested in all cases, eligibility varies widely across states in terms of both income thresholds and categorical eligibility status. Data on Medicaid also include information on the State Children's Health Insurance (S-CHIP or CHIP) program, for some states cover low-income children whose families are ineligible for Medicaid through this program. Data regarding Medicaid policies and regulations come from the Henry J. Kaiser Family Foundation (n.d.a, n.d.b) that maintains a database on Medicaid benefits and an annual report on Medicaid and CHIP eligibility. The data on Medicaid eligibility for immigrants was obtained from the Urban Institute's (2017) State Immigration Policy Resource. Although certain services are mandatory, meaning that states must provide coverage, decisions about copays mean that the functional coverage offered—even for mandatory benefits—can vary by state (Centers for Medicare and Medicaid Services, n.d.).

An additional means-tested assistance program for new and expectant mothers living near or below the poverty line is the Special Supplemental Nutrition Program for Women, Infants and Children (WIC) program (Aussenberg, 2017). A large-scale public health intervention aimed at improving maternal and child health (MCH) outcomes, WIC is a federal program administered at the state-level; however, it was ultimately excluded from the welfare generosity scale because variation (especially across states) was so small as to be rendered meaningless when entered into calculations for the scale. The major exception to this variation arises because of "adjunctive income eligibility," meaning that individuals who are categorically eligible (pregnant, postpartum, or breastfeeding women, and infants and children through Age 5), but do not meet the federal income threshold of 185% of the federal poverty line (FPL), are considered income eligible regardless because they participate in another assistance program (Medicaid, SNAP, or

TANF, or some state assistance programs at the discretion of the state's WIC agency). Although states do have different income thresholds for these programs, the implementation of this policy has only minimal effect on program participation (Carlson, Neuberger, & Rosenbaum, 2017). Furthermore, the varying income thresholds are captured in items pertaining to those programs; therefore, the inclusion of WIC is redundant.

In gathering the information on the programs included in the policy package, I looked at programs across space and time. Longitudinal (i.e., panel) data is required to observe differences not only between states, but also within states over time, and to observe trends in between state differences over time. Therefore, only variables that varied over time and space were chosen. Variables with insufficient variation were excluded from the database because they are unchanging; therefore, they would be invisible once aggregated into a broader measure of generosity. Generosity is a latent variable; therefore, the numbers assigned to it have no inherent value; therefore, I sought only to determine a state-year's relative position to other state-years (Bollen, 2014). Inclusion of these static variables within the scale might well change the absolute values of its score, but would not affect the relative values.

In creating a welfare generosity measure, it was necessary to create a database of administrative practices, regulations, eligibility rules, and benefits for each program. Generosity can vary in a number of ways; a state that covers fewer individuals, but provides greater assistance to them could be considered equally generous as a state that covers a large number of people, but provides a much smaller benefit. In addition to decisions about coverage, generosity also can manifest through program regulations and the degree of bureaucratic red tape that a person would encounter; thus, states that require recipients to jump through many hoops to receive aid could be thought of as less generous owing to a higher degree of administrative exclusion (Brodkin & Majmundar, 2010).

Variables were created according to the information available from the named sources. Variables were most often ordinal, with higher values always corresponding to a more generous policy. Categories were established according to observed patterns in the data; no categories were created that included few or no observations. Cutoffs and categories were created to represented meaningful distinctions according to where the observations actually lay. Binary variables, especially those indicating whether a state had a particular policy or exemption, were coded so that the higher value indicated the more generous answer, regardless of whether the response to the question was "yes" or "no." Continuous variables were treated in the same way: if the more generous state-year would have a lower value for a particular item, that item was recoded so that a higher value again indicated a more generous policy. For each program, the following categories were identified, observed, and measured, using a coding scheme in which higher values designated policies that are relatively "more generous:"

Income eligibility thresholds are limits imposed by each program on an individual's or household's income and assets, representing who is considered poor enough to apply for means-tested aid. States that are more "generous" are those that allow those who have a higher income to receive assistance, and that increase this income threshold because of certain types of assistance units (e.g., those with an elderly or disabled member). States that are more generous also set a higher asset limit or allow more exclusions, which means that they exclude the value of certain items or possessions when calculating someone's total assets. Some states have even eliminated the asset test for some programs, designating them as the most generous in the coding scheme.

Categorical eligibility, in contrast, does not refer to the income of the applicant or recipient, but to their status as a member of a category eligible for a particular program. These requirements often refer to categories such as citizenship status, household composition, or age. Although immigrants are prohibited generally from receiving aid in their first 5 years in the country under federal regulations, states can use their own funds to cover these individuals and they can decide whether to cover them and what categories of immigrants should receive the coverage after the 5-year federal interdiction expires. Pregnant women also are treated as a separate category for the purposes of eligibility for TANF and Medicaid; states vary in what month an expectant mother becomes eligible for a program or becomes eligible under less stringent conditions. TANF allows states to decide on their treatment of minor parents and whether they will allow two-parent households to receive assistance and, if so, under what conditions. States that allow more people in a category to apply for aid (e.g., allowing pregnant women who would otherwise be ineligible to qualify for Medicaid early on in pregnancy) are more generous. In addition, SNAP and Medicaid vary by state in their treatment of single adults, or able-bodied adults without dependents.

Application burden consists of the rules governing how difficult a state makes it to sign up for benefits. More red tape or bureaucratic procedures can be seen as increasing the cost of applying for assistance, even if the cost is not necessarily monetary. Hurdles to enrollment actually decrease the number of people who apply and are accepted; therefore, states that make it easier to enroll or reenroll are coded as more generous. For example, a state that allows broad-based categorical eligibility (BBCE) for SNAP is more generous because a potential recipient does not need to prove that their income is low enough; this is presumed to be the case because they are currently in receipt of another form of aid. Ease of the application process also influences generosity (e.g., telephone interviews instead of in-person interviews, which are easier and therefore more generous).

Conditional requirements refer to the conditions that a recipient must meet or actions they must take in order to (continue to) receive aid. Requirements can include certain behavioral things like immunizations and low school absenteeism for the children of TANF participants; however, the most significant requirements are work requirements and their exemptions. States that allow more activities to be classified as work (or that exempt more categories of people from these requirements) are considered more generous. States with fewer conditions to be met, and states with less severe sanctions for failure to comply, were coded as more generous.

Benefit limits refer policies that restrict access (e.g., the TANF lifetime limit imposed by PRWORA, state-specific lifetime limits, and spell limits). PRWORA limits families who receive federal funds to a maximum of 5 years (60 months) of TANF aid throughout their lifetime. Prior to the passage of PRWORA, some states applied for federal waivers to their AFDC programs and introduced time limits on what was at the time an entitlement program. With the law's passage in 1996, all states had to implement a 5-year time limit, unless they chose to use their own funds. States can individually choose limits that apply to state funds, rather than federal funds. They could also choose to implement a shorter time limit than 5 years. Spell limits refer to the maximum number of consecutive months a household can receive aid, and the existence of a spell limit is considered less generous. With both lifetime and spell limits, the longer the period, the more generous a state is. TANF family cap policies (which limit or prohibit additional assistance to families with the birth of an additional child while on benefits) are also included here.

Benefits or benefit amounts refer to the actual aid that is given to recipients. This refers to the maximum cash benefit allowed to a household under the state's policies; it also refers to the way in which benefits are received. For TANF recipients, cash payments are considered more generous than in-kind goods, vendor payments, or services. When SNAP benefits are rendered as EBT (electronic benefits transfer), a state can be considered relatively more generous because this benefit eases the process of using the benefits and reduces possible stigma. For Medicaid, the number and type of services covered contribute to a state's generosity level. For services whose coverage is mandatory under federal law, generosity is determined according to whether a state requires a copay.

The creation of the data used in generating a scale was a process in which I took all of the relevant variables from the sources mentioned and combined them into a single database that was organized by state and by year. Three different sources were used for the three programs of interest; therefore, not every year since 1996 had data for all three of the programs. I used the years in common in all three sources, 2000–2016.

A number of the variables already existed in binary or categorical format. In these cases, it was simply a matter of ensuring that the coding scheme would work out so that higher values would indicate more generosity and recoding the variables accordingly. A variable that indicated whether a state implemented spell limits on TANF assistance would need to be recoded so that a value of 0 indicated that they do implement these limits, while a value of 1 would indicate that they do not implement them. Certain policies were quantified in such a way that they could be sorted into discrete categories; the results are created or generated categorical variables. For example, in Medicaid benefits, types of services were initially measured in two variables: one indicating coverage and one indicating whether a copay is required. These two variables could be combined into a single categorical variable, where a value of 0 would indicate that the service is not covered; a value of 1 would indicate that the service is covered, but a copay is required; and a value of 2 would indicate that the service is covered without a copay. Some continuous variables needed to be recoded if they measured items in such a way that a higher value would indicate less generosity (e.g., the month of pregnancy in which a woman with no other children first becomes eligible for TANF). These variables were recoded and inverted so that a higher value would always indicate more generosity.

SNAP data were available from the FNS for each month of the year, so I collapsed all 12 observations for a year into one observation, equal to the average of the monthly values. In cases where this collapse put a binary variable's value between two integers, I usually broke it into an additional category in which these values, that indicated a policy was in place or eliminated for part of the year, took on their own unique integer value between the integers indicating whether a policy was in place. For variables with more than two categories in which the intermediate category indicated that the policy was only in part of the state, noninteger values signified that the policy was in place for part of the year either in the entire state or in the whole state. However, it is not immediately apparent from the data what type of change occurred (i.e., going from having a policy in part of the state to having it statewide, or going from having it in none of the state to having it in all of the state). In this case, all noninteger values were understood to indicate "partial coverage" in either the spatial or the temporal sense, or both. A full list of the variables generated using this process, along with a brief explanation of what the variable means and the values it can take on, are reported in Appendix 1.

Ultimately, the database was created of the numerical codification of the rules that were relevant to states' social safety net administration. However, limitations also existed, most notably in identifying and choosing to include the relevant laws. The programs measured excluded Social Security and Medicare, neither of which demonstrate any real degree of devolution to states and whose provision remains centralized at the federal level. As examples of universal social insurance, Social Security and Medicare do not serve the same redistributive function as the programs included in the database; they also represent mandatory rather than discretionary federal spending. Therefore, they are unlikely to vary as dramatically because of the political or economic climate. Although these programs were excluded because they are universal (rather than means-tested), when they are combined they make up the bulk of the American assistance landscape, accounting for 45% of federal program expenditures in 2018 (Social Security and Medicare Boards of Trustees, 2019). The exclusion of programs like Social Security, Medicare, and WIC means that scholars who might hope to look at the effects of those programs cannot properly do so using these data.

Furthermore, coding decisions had to be made and sometimes-arbitrary cutoffs were imposed to create an ordinal scale for most variables. Although the decisions could have been made according to the data at hand, the choice of where to make a dividing line along the spectrum of different policies was always arbitrary to a degree. Although some rules lend themselves to simple binary (yes/no or 1/0) classifications, many more variables had to be constructed into an ordinal scale, and the choice of how to cluster the different rules along this scale had to be made by an individual and was not inherent to the data. Additionally, although quantitative data provide a rich panoply of research opportunities, a database such as this database did not lend itself to particularly nuanced examinations of individual programs or states. Although quantitative data are a valuable tool, they cannot substitute entirely for thoughtful qualitative studies.

Section 1.4 Social Determinants of Health

Public health law in the United States addresses the legal powers necessary to ensure the health and welfare of populations as a function of good governance and rule of law ((Gostin & Wiley, 2016). With law creating the conditions for people to be healthy, public health law defines distributive justice in the distribution of resources for public health (Parmet, 2009). In understanding the role of law as a basis for health, public health law researchers examine "direct relationships between law and health, and relationships mediated through the effects of law on health behaviors and other processes and structures that affect population health" (Burris, Wagenaar, Swanson, Ibrahim, Wood, & Mello, 2010). Drawing on research on public health systems and services research, which studies "the organization, finance, and delivery of public health services," public health law research has come to embrace empirically rigorous research methods from the social sciences to explore the causal effects and influences of law on public health systems, practices, and outcomes (Burris, Mays, Douglas Scutchfield, & Ibrahim, 2012; Mays, Halverson, & Scutchfield, 2003; Mello & Zeiler, 2008).

Public health law researchers consider law as a determinant of public health and seek to test empirically the direct and indirect effects of law on public health outcomes (Burris, 2010). In such public health law, researchers seek to assess

- the factors that affect whether laws are enacted (policymaking studies),
- the content of the existing legal landscape (mapping studies),
- the actual implementation and enforcement of the law (implementation studies),
- the effects of the law on public health (intervention studies), and
- the ways in which the laws affect health (mechanism studies). (Burris, Ashe, Levin, Penn, & Larkin, 2016).

According to Ramanathan, Hulkower, Holbrook, and Penn (2017), these intervention studies have come from the basis of the new field of “legal epidemiology” (p. __), scientifically studying “law as a factor in the cause, distribution, and prevention of disease and injury in a population” (p. 69). Examining the effects of the law on public health, such legal epidemiology is seen as necessary to provide empirical evidence that will help (a) to determine whether laws have the intended effects on public health and (b) to implement laws to improve public health (Burris et al., 2010).

In approaching this inherently interdisciplinary research, researchers have employed a range of qualitative, quantitative, and mixed methods that have employed experimental, quasi-experimental, observational, or participatory designs (Burris, Ashe, et al., 2016). Although researchers long employed qualitative methods to analyze the law’s impact on health outcomes, the recent trend has been toward quantification to assess the impact of public health law on health outcomes, thereby justifying public health law reforms (Burris, Ashe, et al., 2016).

This “policy surveillance” has drawn on coding methodologies to measure the characteristics of public health laws (Burris, Hitchcock, Ibrahim, Penn, & Ramanathan, 2016). Analytic coding methodologies have taken root in public health law research, allowing for the systematic examination of the content of public health laws (Anderson, Tremper, Thomas, & Wagenaar, n.d.). Coding is a way to label and organize qualitative data (Green & Thorogood, 2009). Especially where researchers are interested in analyzing a relatively abstract policy feature (e.g., “generosity”), these coding approaches help to identify in a deliberate manner the key ideas, themes, or core concepts that make up the variable of interest in a research question (Guest, MacQueen, & Namey, 2012). Coding approaches can also be applied to categorize more concrete policy concepts. For instance, clearly defined rules can be captured quantitatively in binary or nominal/categorical variables that describe the presence or absence of certain policy features. Additionally, where policy exhibits rules that convey a clear order or varying degrees of intensity, these features can be converted to ordinal (or potentially even continuous) variables and used for analysis.

Such coding allows for the systematic identification of characteristics of a law, providing a means to organize, correlate, and analyse themes across a set of laws (Burris et al., 2010). Beyond simply identifying the changes associated with the presence or absence of a law, coding facilitates the evaluation of the impact of specific and various dimensions of policy that often vary across jurisdictions (Pacula, Powell, Heaton, & Sevigny, 2015). Moreover, this approach to public health law research creates a platform to conduct statistical analysis and builds a valuable bridge between qualitative and quantitative (or econometric) methods of research.

- Program evaluation – identifying the causal impact of a rule/policy/law change on an outcome.
- Helps research move from simple associations to causation (see Burris et al., 2016, p. 14)
- Can identify total and partial effects (depending on whether statistical models control for mediators).
- Can identify differential effects across various groups (i.e., heterogeneous treatment effects between men vs women, between different age ranges, and between race groups).

Such program evaluation has significance in informing legislative decisions on policy reforms, identifying intervention points according to the aspect of welfare eligibility rules that drive health outcomes and, thereby, overcoming components of the law that hinder public health outcomes. As a basis for future research, such comparative coding of quantitative state data can guide research questions for more detailed qualitative studies at state-level.

Section 1.5 Limitations and Future Applications

Of course, the process of quantifying rules and regulations is not a simple one. Identifying the policies of interest poses difficulty and different research has been used to identify different methods of policy selection. Stacy et al. (2018), in creating the SNAP Policy Index for the USDA, focused on policies that have shown a statistically significant effect on the SNAP caseload. McKernan, Bernstein, and Fender (2005), in looking at TANF policies, emphasized the importance of identifying a typology prior to the quantification process; they advocated basing this on an outcome because "not all policies are hypothesized to affect all outcomes. Organizing policy typologies around outcomes thus reduces the complexity of welfare policies by limiting the number of policies in a typology" (p. 445). The strength of the database in this study is that it can be used to collect as much information on policies as is freely available from existing sources, with the opportunity to add additional policy information as it becomes available. Therefore, it is a relatively simple process to select the policies that might affect the outcome of interest for further analysis, either by aggregation into an index or other, more complex, processes such as factor analysis or cluster analysis.

However, this study database is limited by the availability of information on these program regulations. Longitudinal quantitative analysis relies on repeated measures of the same indicators across time, yet a number of indicators contain no data before or after a certain period (e.g., the implementation of the Affordable Care Act (ACA) of ____ led to a number of changes in Medicaid indicators). Quantitative analysis also exploits variation, across either time or space, which is why I failed to include the WIC program; however, other types of analysis that do not rely on this variation would benefit from the inclusion of such programs. The actual quantification procedure is also prey to the loss of information necessary in rendering nuanced information numerically. Not all policies lend themselves to clear bifurcation or division into categorical variables. Decisions about where to render cutoff points for division into ordinal variables were made according to an examination of the existing data, but they are inherently arbitrary. Additionally, by collapsing a variety of policy implementations into a single value, some information that was possibly of interest was necessarily lost.

The database was generated with the aim of evaluating the effect of social assistance on birth outcomes, and the programs included were selected with that in mind; therefore, likely programs and policies of relevance to public health researchers were not included here (e.g., housing assistance). Furthermore, the programs selected represent only the federally funded (or mostly federally funded) safety net; however, states establish their own programs outside of this safety net. A comprehensive analysis of all social assistance would ideally include state-level assistance such as state EITCs. Nevertheless, the existing database as well as the methodology behind it will enable further research on the impact or effectiveness of welfare law on a number of public health outcomes, birth outcomes being only one example.

Perhaps the biggest weakness of this database is a shortcoming inherent to quantitative policy research as a whole: the existence of a law or policy does not guarantee its uniform implementation as written. The social safety net generosity index is meant to measure the social assistance climate to which recipients are subject, but that climate depends on more than merely the policies themselves: it depends on how they are implemented. The experience of recipients in the United States depends on more than where one lives: it depends on with whom one interacts; therefore, the discretionary application of laws can change the way in which they affect the public. Employees responsible for administering the safety net and implementing the policies written have a large amount of discretion in how they go about doing their jobs, and this discretion can mean the difference between being accepted to a program or being denied (Lipsky, 1971, 1980; Riccucci, 2005a, 2005b). These "street-level bureaucrats" have an equal impact on the experiences of those who rely on the safety net as the actual regulations; however, it is impossible to quantify this part of the experience.

Although policy surveillance, analytic coding, and quantitative scales are indispensable to understanding the policy landscape of welfare generosity, quantitative methods cannot displace qualitative research—especially where binary indicators miss out on the specificity of policy variables. Instead, they can support other methods of analyzing public laws through larger datasets that can be analyzed across states and over time.

Conclusion: Everyone Should Code

Ultimately, social scientists in any field can make use of this methodology to examine the impact of changes in policy or related rules and regulations. The quantification of social safety net laws allows social and health policy researchers to assess the correlation of social welfare eligibility rules with health outcomes, providing evidence of policy impact. Statistical or econometric analysis can often bolster and complement existing qualitative research, or give credibility to anecdotal evidence. In an era of retrenchment and funding cuts for safety net programs, it is important to provide policymakers with evidence of the effectiveness of these programs not only on the recipient's economic status, but also on the health of the total population.

Going forward, using established methodologies for gathering such evidence will be crucial for policy scholars. Established methods for quantitative coding of state rules and regulations are needed, and it is my hope that this database and its use in generating welfare generosity indicators can help to establish those methods. With this database I hope to begin bridging the gap that exists between the fields of public health and political or policy methodology. In making this data available to other researchers, I hope that social and health policy scholars interested in establishing the effectiveness of certain policies on public health outcomes can take advantage of this wealth of data as well as the sophisticated aggregation techniques developed for use in policy analysis and political science.

PAPER 2: CREATING A GENEROSITY SCALE: AGGREGATING SOCIAL SAFETY NET RULES

Introduction

The database of safety net policies created in Paper 1 can be used in a variety of different ways. In Paper 2, I use the data to construct two generosity measures. In Section 2.1, I examine the ways in which the resulting data can be merged into a single measure or score, quantifying social safety net generosity for each state in each year of the period by program, and allowing for comparative social policy analysis across states and over time. I discuss two procedures for aggregating the database into a single score, either by creating a generosity index, which measures the social assistance climate experienced by recipients, or a generosity scale, which measures the underlying or motivating generosity that causes changes to the policies.

For the index, I simply took an average of all the indicators to create a measure of generosity in each state in a given year, while for the scale, I used statistical techniques and theoretical knowledge about the programs to develop a way of weighting the indicators from the database for a combination into a single measure. In Section 2.2, I demonstrate the construction of the social policy index, and in Section 2.3, I discuss the construction of the generosity scale using the database from Paper 1. In Section 2.4, I discuss the results of the index, and In Section 2.5, I present the results of the factor analysis. In the final section, I discuss the implications of these results for future research, as well as their limitations, before concluding that the naïve index is currently the best aggregate measure for use in quantitative analysis.

Section 2.1 Aggregating the Data: Scale Versus Index

The items included in the database are the rules and regulations that were made by the state regarding decisions such as eligibility thresholds for assistance or what services to offer low-income individuals, which are manifest variables in that they can be observed and measured. The next step was to aggregate these data into a single number that could be thought of as a crude measure of generosity in a state-year. Beyond using these directly observable variables to manifest a latent concept, the combination into a scale had the advantage of collapsing a large number of items into one score: the purpose of aggregating the data contained in this database was to create a single measure that would allow a comparison across time and space. Rather than include numerous measures that would be related to each welfare program in an analysis, this methodology allowed me to combine the data relating to program administration, benefit amounts, and eligibility requirements into a single measure for each state-year. Using the measure as a sole proxy for generosity allowed for the inherent benefits of parsimony (Harman, 1976); furthermore, the manifold determinants of generosity, that vary slightly over time and across states, were absorbed in this scale. Any changes in rules, bureaucracy, benefit levels, or eligibility were reflected in the measure: changes could be seen as rendering a state-year more or less generous.

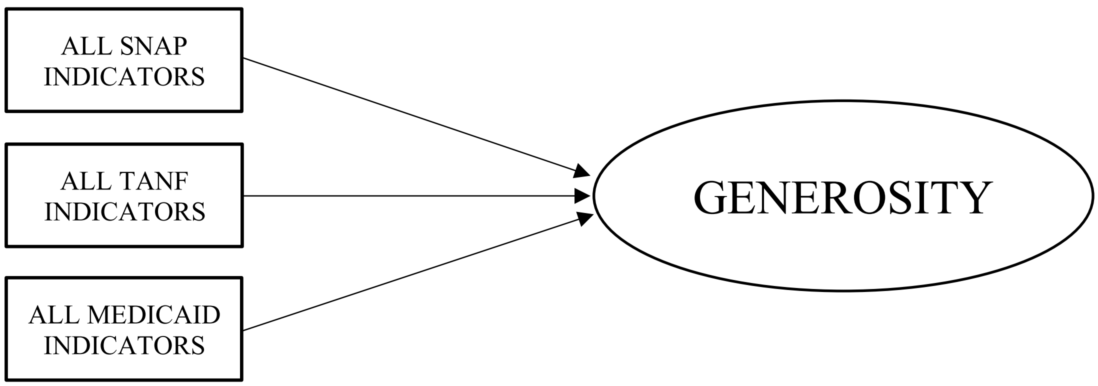
With the generosity scale, I attempted to measure how generous a state was in a given year. Where "generosity" was the underlying concept, the rules governing the program administration and benefits were the observable items that I could use to illuminate it. The generosity of the social assistance climate was an unobserved, or latent, characteristic of a state-year in that it could not be directly measured (Jöreskog & Sörbom, 1979). However, this generosity could be thought of in two different ways: as causing the policies, and as the result of these policies. The difference was subtle, but important in that it affected the procedure of aggregating the data into a single measure.

If generosity were to be thought of as the “temperature” of the state’s social assistance climate, it would be caused by changes in policies and rules surrounding assistance programs. Generosity in this sense is something to which aid recipients are subject, and it is a measure of their experience or environment. If generosity is truly a climate that is experienced by recipients and caseworkers, the best analogy for a measure of this latent variable is the heat index. According to the National Weather Service (n.d.), the heat index “is what the temperature feels like to the human body when relative humidity is combined with the air temperature.” The heat that one experiences is determined by the temperature and humidity, and both of these observed variables are combined into an index whose score is a more accurate assessment of the conditions experienced by individuals.

In this analogy, the generosity index represents what is experienced by the recipients, and it is composed of measurable observed items, that is, the rules and regulations governing welfare programs. The variables contained in the assembled database are “cause indicators” in that their values determine the level of the latent construct rather than the other way around (DeVellis, 2012). Changes in program rules and requirements represent the cause of a change in latent generosity. In this framework, the indicators or observed variables do not themselves need to share a common cause (e.g., variations in Medicaid coverage might be the result of different factors than variations in TANF services), However, they do result in a common effect, a change in the generosity experienced by recipients living in that state at that time. This framework also allowed indicators to change independently of each other, causing a change in generosity. If work requirements were to become stricter, but Medicaid eligibility remained unchanged, the generosity value would still change along with the work requirement indicators.

Figure 2.1

Conceptual Model of Generosity Index

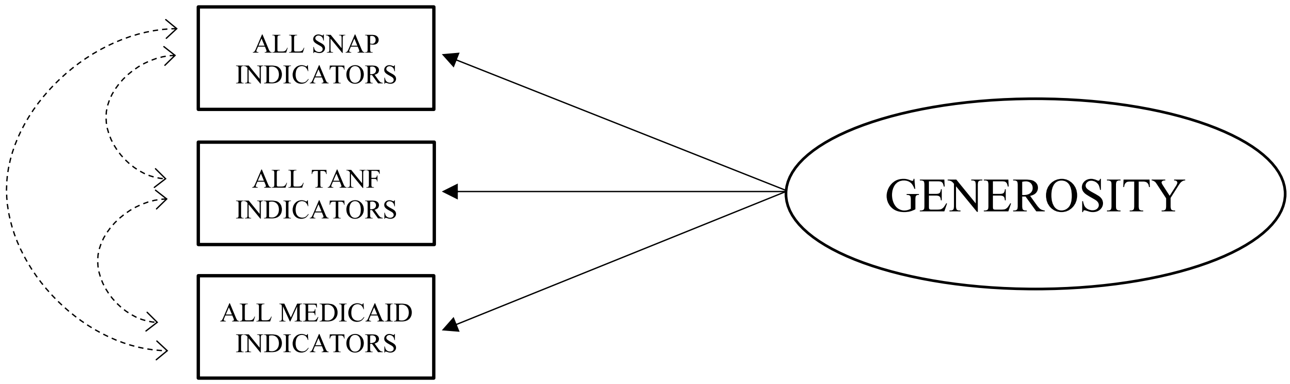


To return to the weather analogy, the cause indicators can be thought of as the temperature in degrees or the humidity percentage; that is, they are observable and measurable facts about the environment, and it is these observations or measurements that are contained in the database. Generosity is analogous to the heat index in that these observations are combined into a single number and represents how someone subject to it experiences the environment. Much like the reason one feels hot on a given day is a result of the measured temperature in degrees as well as the humidity, how “generous” one’s state feels to an aid recipient is the result of TANF requirements, SNAP rules, and Medicaid restrictions.

However, using a scale assumes that causality occurs in the opposite direction from an index. The presumption is that the latent generosity in a state directly causes the item values included in the scale; that is, program rules and administration vary because of this underlying generosity (Cohen, Cohen, Teresi, Marchi, & Velez, 1990; DeVellis, 2012). Items in a scale are more likely to correlate with each other, and they are certainly related in that they have a common cause. Latent generosity is not akin to a temperature or climate experienced by those living in the environment, but rather it is an underlying mood or feeling in the state that affects how policymakers design program rules to allow for greater or lesser access to aid.

Figure 2.2

Conceptual Model of Generosity Scale



Section 2.2 Construction of the Index

The construction of an index in this case did not require any psychometric or probabilistic techniques to combine or reduce the data. What I have called a "naïve index" is simply a score between 0 and 1 in which a higher value indicates more generosity. To generate this index, each variable in the database was converted to a scale of 0–1. Binary variables were left in their current 0/1 format and categorical variables were recoded so that the highest value (i.e., most generous policy) would correspond to 1 and other values would fall in between. A variable with five categories that was previously coded as 0/1/2/3/4 became coded as 0/0.25/0.5/0.75/1. A continuous variable can be recoded in a similar way, being divided by its maximum possible value so that each value would represent a proportion of the greatest generosity possible for that item (where a higher value would indicate less generosity, these proportions were then subtracted from 1).

In a few continuous variables, the maximum possible value for the indicator did not indicate the most generous policy choice even when a higher value was more generous. For example, asset limits are more generous the higher they are. An asset limit represents the maximum value of a household's assets before it are disqualified from assistance, for a large value of assets held by someone precludes the government from seeing them as in need of aid, even if that individual has low earnings. Assets include things such as the vehicles owned by the people in the household or money held in their savings accounts. States that allow higher asset limits are more generous because they allow more households to qualify; however, the state-year with the highest value asset limit does not represent the most generous policy because some states have chosen to eliminate the asset test. For variables such as this, each value was divided by the maximum possible value of that variable; the resulting value was then multiplied by 0.9. A value of 1 was reserved for the most generous policy possible, for example the elimination of the asset test.

Although similar to what was done by the USDA to construct its own SNAP index, my process was slightly more complex than the USDA's. Although the USDA's SNAP Policy Index was created simply by adding or subtracting a unit for each policy adopted in a state-year according to whether it accommodated or encouraged SNAP participation, the USDA's index contained only binary indicators (Stacy et al., 2018). My data contains categorical variables with more than two categories as well as a number of continuous measures; therefore, I converted everything to fall between (0) and (1).

Once every variable in the database takes on a value from 0–1, they could be aggregated in any number of combinations to form an index of generosity by simply taking an average of the chosen variables in each state-year. A naïve index can be constructed using all the variables and measuring the climate for all assistance; similarly, it can be created for each individual program to take the temperature of the Medicaid climate or the TANF climate. Programs can be further broken down, with indices measuring particular program aspects (e.g., eligibility criteria or administrative exclusion). Although the naïve index simply uses an average of the 0/1 scores, it is possible to subject these variable scores to different weighting schemes. Depending on what is to be measured, one can use their substantive knowledge of the policy landscape to develop deterministically these weights. For example, to look at how generosity affects immigrants' health or experiences, one might weight immigrant eligibility criteria more heavily.

The naïve index contains a total generosity score as well as three program scores; these program indices in turn were generated by averaging their subindices. Each program contains different subindices. The SNAP index contains the fewest subindices (at only two); it is composed of a measure of eligibility and a measure of administrative burden or administrative cost. The Medicaid program index is a combination of four subindices: administrative burden, benefit generosity, eligibility, and rules for immigrants. The TANF program index contains four subindices: applicant processes, behavioral conditions, benefit receipt, benefit limits, and work requirements.

Section 2.3 Constructing a Scale

Unlike the index, scale construction uses theory to drive the process. In deciding on the next steps in the construction of the social safety net generosity scale, exploratory factor analysis (which uses statistical methods to create latent variables or classes that exist because of correlations in the data) was rejected in favor of confirmatory factor analysis (which specifies in advance a pathway through which the latent and manifest variables are related; Bollen, 2014). To create this scale, knowledge of the American social and health policy landscapes, as well as existing theories in political science and public administration, were used to hypothesize the relationship between generosity and the items measured, notably through intermediate latent variables.

The key distinction between the two different methodologies is that exploratory factor analysis is used to search the data for underlying patterns without a theoretical justification; all of the observed and unobserved variables are allowed to correlate with one another and the number of latent variables is not specified in advance. However, confirmatory factor analysis begins with "a detailed and identified initial model" (Bollen, 2014, p. 28).

Three models are proposed as possible ways in which generosity and program policies are related. Each model contains different intermediate latent variables that are all related to generosity, but that do not all relate to every item measured. Instead, observed items were divided into different categories, each of which relates to generosity through a different intermediate latent variable. The three possible models follow:

- Program model: This model hypothesizes that generosity affects each program differently. Consequently, the observed variables are divided into three groups that correspond to three intermediate latent variables, each one representing a different assistance program.
- Coverage model: This model focuses on the possible tradeoff between the number of people covered (breadth) and how generous the benefits provided to those people are (depth). The intermediate latent variables are breadth and depth and the observed variables are assigned to one or the other category (or possibly both, for some items) depending on whether a more generous response to that item implies that the benefit received is more generous or that more people will be able to enroll or remain in the program.

- Administrative model: This model distinguishes between observed items that represent benefit levels and those that represent administrative hurdles for recipients and social services employees. Items representing bureaucratic red tape or administrative hassle represent generosity in that increased hassle discourages program participation through administrative exclusion. (Brodkin & Majmundar, 2010)

The variables that were included in the factor analysis were rescaled so that all of the categorical variables took on integer values only. A variable that might initially have taken on the values 1, 1.5 or 2 was recoded to take on the values 1, 2 or 3 to avoid problems when running the models in MPLUS.

Following is a description of the steps undertaken to construct the Program Model of Generosity. A similar process, in which variables were added a few at a time to create intermediate latent variables before those intermediate variables were combined into the hierarchical models illustrated in Figures 2.3–2.5, was undertaken for each of the three hypothesized models. For the sake of brevity, full descriptions of model construction for all three models, as well as for all intermediate latent variables, are not included here because the steps undertaken were similar to those described in the following paragraphs.

Program Model Construction

Construction of the program model began by assembling a model for SNAP. The continuous latent variable that was meant to embody the concept of generosity within the food stamp program was analyzed with 14 indicators from the SNAP program. Upon first running a CFA of just the SNAP generosity latent variable by all 14 indicators, I determined that FS11 (or a variable measuring whether a state requires finger-printing of applicants) was negatively correlated with a number of other indicators. The variables were coded such that a higher value would indicate a more generous policy; therefore, all of the variables should be positively correlated.

It is unclear why finger-printing would be inversely correlated with every other indicator of generosity within the food stamp program, but upon closer examination of the data, finger-printing appears to have only ever required in five states: Arizona, California, Massachusetts, New York, and Texas. This correlation was negative; therefore, the requirement of finger-prints does not seem to be an especially effective indicator of any underlying generosity in the SNAP program, which was what the latent variable was intended to measure. Therefore, it was excluded from the analysis.

After inputting the SNAP variables into MPLUS, it was necessary to check that the factor loadings indicated statistical significance within the model ($p <= 0.5$; for all SNAP indicators the factor loadings had p values of 0.000). Then the R^2 estimates were checked for significance as well; once again, for all included indicators, the two-tailed p value was approximately 0.000. The model fit was then improved by allowing the measurement errors of certain variables to correlate with one another. FS04 and FS05 are both variables that indicate whether a face-to-face interview is required for certification. FS04 indicates whether this is a requirement for initial certification and FS05 indicates the requirement for recertification. It makes sense that these data are gathered from the same place; therefore, if any measurement error exists in one place, a similar degree of measurement error will likely exist in the other place.

Other measurement errors were allowed to correlate with one another, although there is a less obvious reason for their indicators to suffer from similar types of measurement error. These variable pairs indicate (a) whether a state used a simplified reporting option for households with earnings in a particular year (FS06), (b) which vehicles, if any, or up to what value of a vehicle would be exempted from counting toward a household's asset limit (FS07), (c) whether a state operated a combine application program (CAP) for Supplemental Security Income (SSI) recipients to apply for SNAP (FS02), and (d) the average length of the certification period in a state (FS09). Standardized results for this intermediate model can be found in Table 2.6. Figure 2.25 is a diagram that indicates the structure of these results.

The next step in constructing the program model was to repeat the process that had already been undertaken on the SNAP program to generate the intermediate latent variables TANF and Medicaid. The results of these single latent variable models indicated a somewhat poor fit, particularly for the Medicaid variable; therefore, a combination of the three programs into the hierarchical model proposed in Figure 2.3 was not carried out.

Additional Model Construction

The indicators chosen for inclusion in the intermediate latent variables shown in Figures 2.4–5 are indicated Table 2.1.

Table 2.1

Factor Analysis Variables

Variable	Definition	Coverage model	Admin model
FS01	Does SNAP use BBCE?	Breadth	Admin
FS02	Does SNAP streamline the application process for SSI recipients?	Breadth	Admin
FS03	What percentage of SNAP benefits use EBT cards?	Depth	Admin
FS04	Does the state allow a telephone interview instead of face-to-face for initial SNAP certification?	Depth	Admin
FS05	Does the state allow a telephone interview for SNAP recertification?	Depth	Admin

Variable	Definition	Coverage model	Admin model
FS06	Does the state allow a simplified reporting option for household income for SNAP?	Depth	Admin
FS07	Are the value of vehicles excluded from the SNAP asset test?	Breadth	Benefits/ eligibility
FS08	To what extent does SNAP cover noncitizens?	Breadth	Benefits/ eligibility
FS09	What is the length of the average period for which a SNAP household is certified eligible?	Depth	Admin
FS10	Does the state operate SNAP call centers?	Depth	Admin
FS11	Does the state require fingerprinting of SNAP recipients?	Depth	Admin
FS12	Is there an online SNAP application?	Depth	Admin
FS13	Does the state do any SNAP outreach?	Depth	Admin
FS14	Does the state offer transitional SNAP benefits?	Depth	Benefits/ eligibility
TANF2PAR	Are two-parent households eligible for TANF assistance?	Breadth	Benefits/ eligibility
TANFA1	What is the asset limit for TANF applicants?	Breadth	Benefits/ eligibility
TANFA2	Is the TANF applicant asset limit higher for households that contain an elderly or disabled member?	Breadth	Admin
TANFA4	What is the asset limit for TANF recipients?	Breadth	Benefits/ eligibility
TANFA5	Is the TANF recipient asset limit higher for households that contain and elderly or disabled member?	Breadth	Admin
TANFBN6	What is the maximum monthly TANF benefit for a family of three?	Depth	Benefits/ eligibility
TANFBV0	How many behavioral conditions are imposed upon TANF recipients?	Depth	Admin
TANFD5	Does receipt of a diversion payment lead to a period of ineligibility for TANF following that payment?	Breadth	Benefits/ eligibility

Variable	Definition	Coverage model	Admin model
TANFD6	Does receipt of a diversion payment count towards the TANF lifetime time limit?	Depth	Benefits/ eligibility
TANFD9	What form do TANF diversion payments take?	Depth	Benefits/ eligibility
TANFF1	Does the state impose a cap on family size for TANF benefits?	Depth	Benefits/ eligibility
TANFIM0	Does the state provide TANF coverage to immigrants beyond that which is covered by PRWORA?	Breadth	Benefits/ eligibility
TANFINC1	What is the income limit for TANF applicants?	Breadth	Benefits/ eligibility
TANFJS	Is a job search required upon application for TANF?	Depth	Admin
TANFL1	How long is the lifetime limit for receipt of TANF assistance?	Depth	Admin
TANFL2	When the TANF lifetime limit is reached, whose benefits are terminated?	Depth	Benefits/ eligibility
TANFL3	Does the state impose spell limits on TANF assistance?	Depth	Admin
TANFPREG	In which trimester of pregnancy is a woman with no other children eligible for TANF?	Breadth	Benefits/ eligibility
TANFSC3	What is the most severe sanction that exists for noncompliance with TANF conditions?	Depth	Benefits/ eligibility
TANFTEEN	Can minor parents be considered the head of TANF households?	Breadth	Benefits/ eligibility
TANFWR1	When must work participation begin for TANF applicants?	Depth	Admin
TANFWX0	How many exemptions exist to TANF work requirements?	Depth	Admin
MCAD01	How long is the wait length for Medicaid enrollment?	Depth	Admin
MCAD02	Has the state eliminated face-to-face interviews for Medicaid for SSI recipients?	Depth	Admin
MCAD03	Has the state eliminated face-to-face interviews for Medicaid for parents?	Depth	Admin

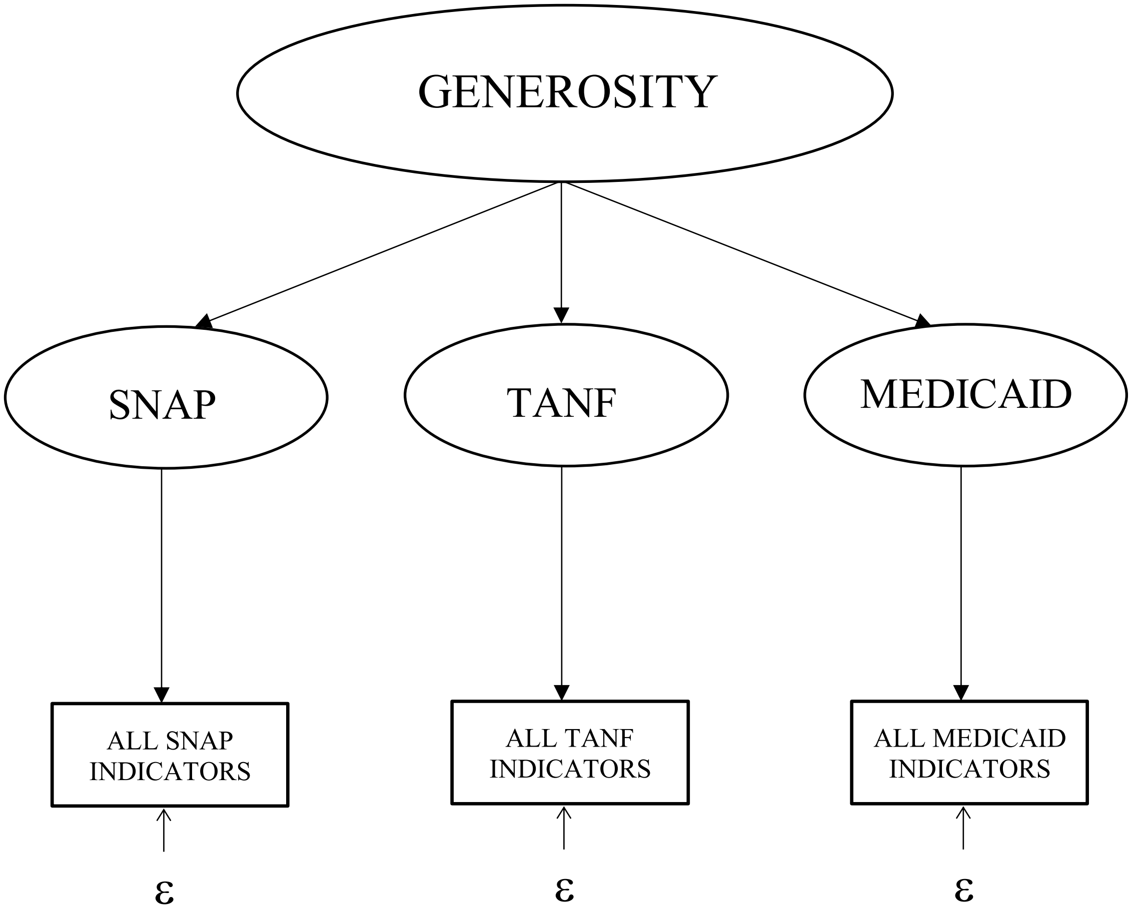
Variable	Definition	Coverage model	Admin model
MCAD04	Has the state eliminated the Medicaid asset test for all recipients?	Breadth	Admin
MCAD05	Has the state eliminated the Medicaid asset test for parents?	Breadth	Admin
MCAD06	Does the state presume Medicaid eligibility for SSI recipients?	Depth	Admin
MCAD07	Does the state presume Medicaid eligibility for pregnant women?	Depth	Admin
MCAD08	Does the state have continuous eligibility for Medicaid?	Depth	Admin
MCAD09	Has the state eliminated face-to-face interviews for Medicaid renewal for all recipients?	Depth	Admin
MCAD10	Has the state eliminated face-to-face interviews for Medicaid renewal for parents?	Depth	Admin
MCAD11	How frequently must all Medicaid recipients renew their eligibility?	Depth	Admin
MCAD12	How frequently must parents renew their Medicaid eligibility?	Depth	Admin
MCBOPAV	To what degree does a state cover optional Medicaid services?	Depth	Benefits/ eligibility
MCEL01	What is the Medicaid income limit for children less than one year of age?	Breadth	Benefits/ eligibility
MCEL02	What is the Medicaid income limit for children between one and five years of age?	Breadth	Benefits/ eligibility
MCEL03	What is the Medicaid income limit for children between six and eighteen years of age?	Breadth	Benefits/ eligibility
MCEL04	What is the Medicaid income limit for pregnant women?	Breadth	Benefits/ eligibility
MCEL05	What is the Medicaid income limit for parents?	Breadth	Benefits/ eligibility
MCEL06	What is the Medicaid income limit for able-bodied adults without dependents?	Breadth	Benefits/ eligibility

Variable	Definition	Coverage model	Admin model
MCIM99	To what extent does Medicaid cover noncitizens?	Breadth	Benefits/ eligibility
MCMANDCO	How many mandatory Medicaid services require a copay?	Depth	Benefits/ eligibility
MCRX	Do prescription drugs require a copay?	Depth	Benefits/ eligibility

Note. BBCE = broad-based categorical eligibility; EBT = electronic benefits transfer; FS = Food Stamps; MC = Medicaid; PRWORA = Personal Responsibility and Work Opportunity Reconciliation Act; SNAP = Supplemental Nutrition Assistance Program; SSI = Supplemental Security Income; TANF = Temporary Assistance for Needy Families.

Figure 2.3

Program Model Conceptualization of Factor Analysis



Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance for Needy Families.

Figure 2.4

Coverage Model Conceptualization of Factor Analysis

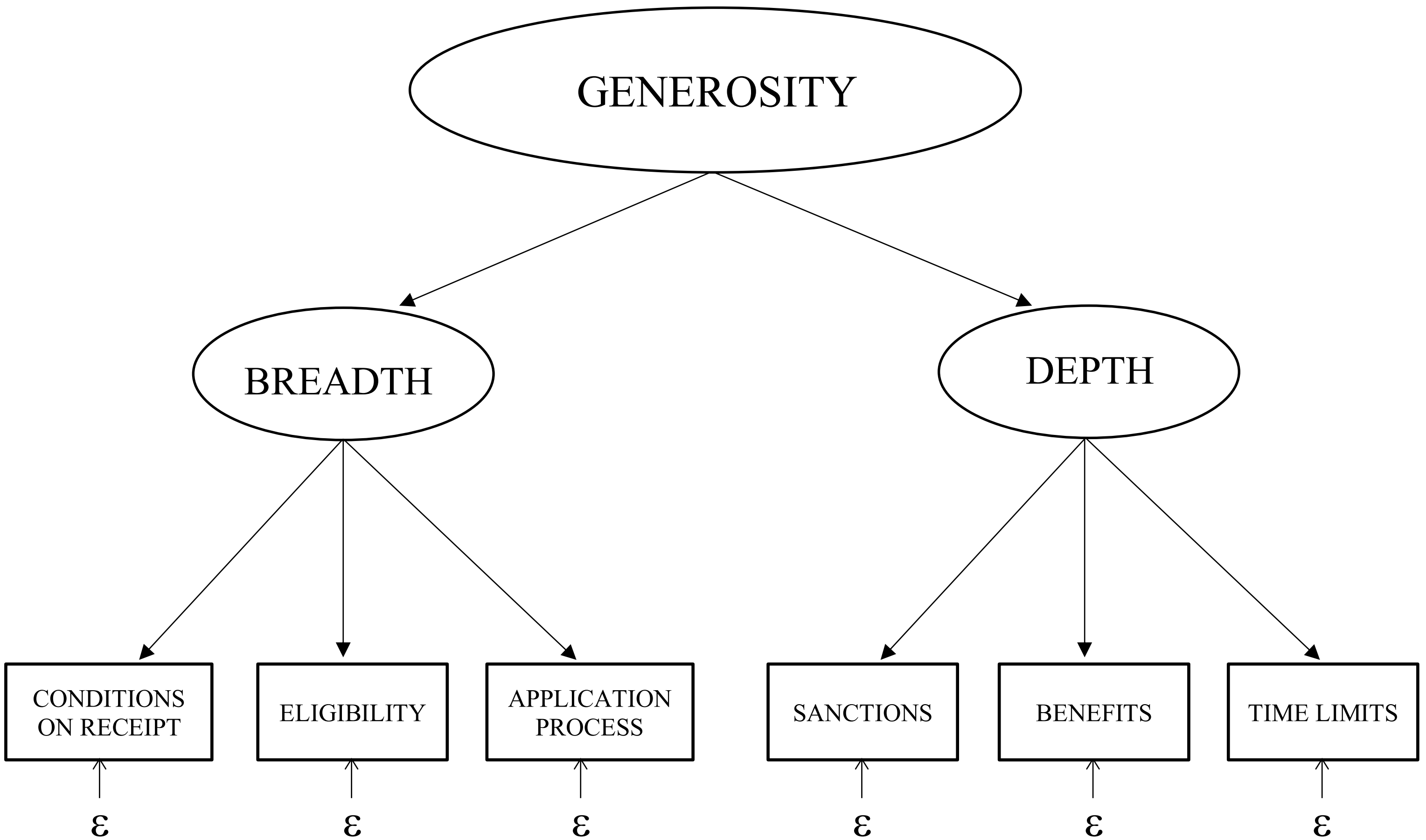
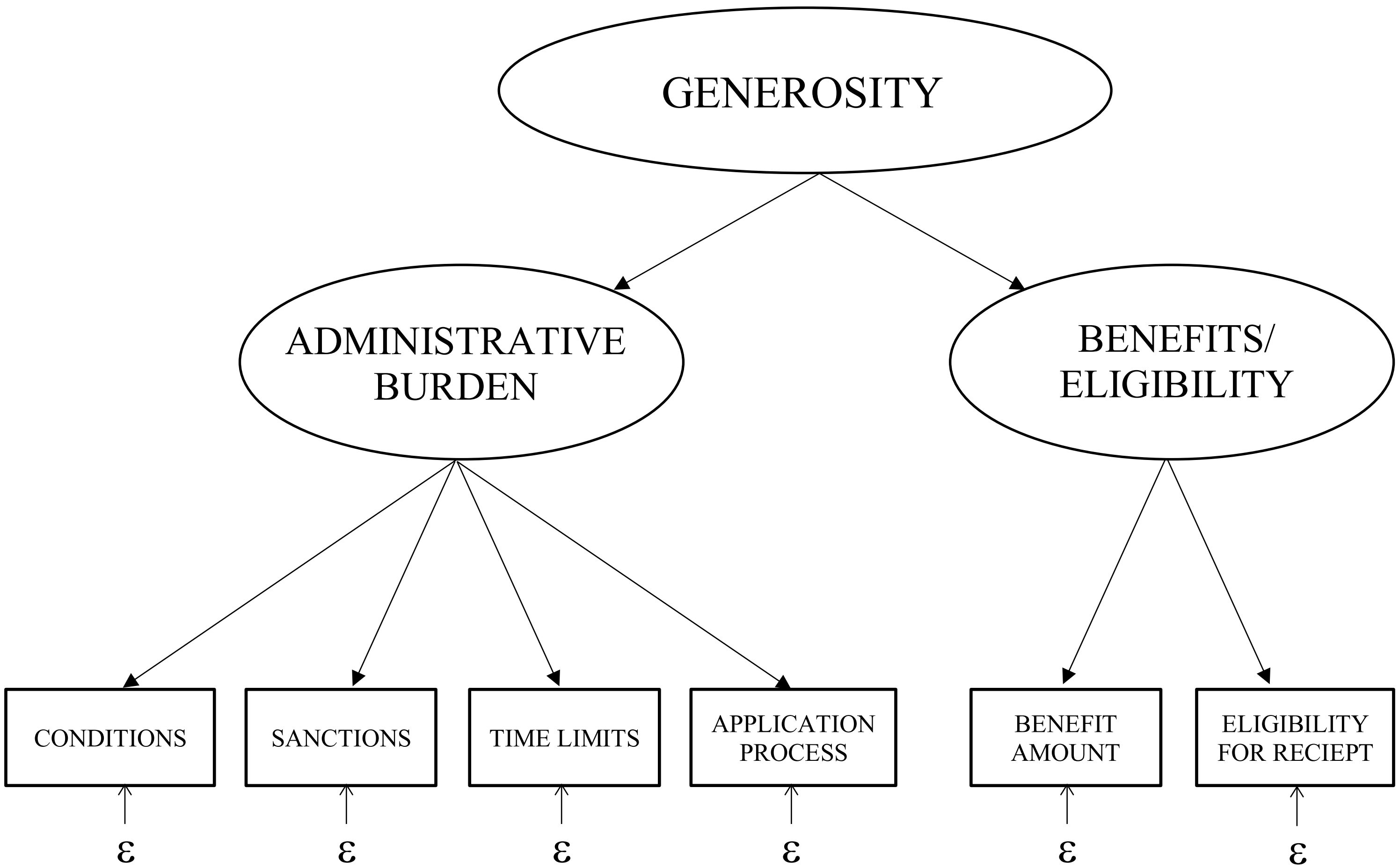


Figure 2.5

Administrative Model Conceptualization of Factor Analysis



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Section 2.4 Results of the Index

The initial indices are unweighted. An average was generated for the SNAP program, another average for TANF, and another average for Medicaid. The three program indices were averaged together into the total social safety net generosity index. Although the total generosity score was a composite of all three program scores, the absolute values of these four indices could not be compared to one another. For example, the TANF generosity index was consistently lower in value than the other three indices; however, this did not automatically mean that TANF policies are less generous than SNAP or Medicaid policies. Instead, each index's scores are comparable only to its other values in different states or years. Tables and graphs of these index scores across states and years are available throughout this paper and in the appendix.

Key Result 1: States Are Getting More Generous Over Time

Averaged over all 50 states and the District of Columbia, total generosity increased from 2004 to 2016; however, it did not increase monotonically (see Figure 2.6). This was true of the SNAP and TANF generosity indices as well; however, Medicaid generosity, with the exception of an extremely tiny decrease from 2011 to 2012, actually did increase each year.

Looking at the results of the naïve index shows largely what one expects to see: over time, generosity is mostly increasing. Although it might have increased because of the increased dollar values of benefit award amounts, benefit limits, and means-tests as the years progress, which might lead states to score within a higher category for certain variables (e.g., applicant asset limits), the vast majority of indicators making up the index concern policies and procedures, rather than with actual amounts. Within the three program indices, subindices measuring TANF behavioral conditions or the Medicaid eligibility for different categories of immigrants are increasing on average from 2004–2016, despite containing no measures of dollar amounts.

The top 10% of all state-year observations on each program index and the total generosity index contain observations from every year after 2004, and the top 10% of TANF and Medicaid observations also contain some from 2004, which does not support the idea that generosity grows over time (see Figures 2.9–2.16). However, the bottom 10% of all observations on the four indices are rather different and do seem to indicate generosity growth over time. Only Medicaid and TANF have observations in the bottom 10% that occur after 2011, although for Medicaid, those observations in 2014–2016 are only from Mississippi, which has the lowest Medicaid generosity score in ever year (see Figure 2.16). In fact, the 10 lowest Medicaid generosity scores across all state-year observations are all from Mississippi from 2004–2013. Only in 2014, does Mississippi's Medicaid generosity finally exceed Alabama's Medicaid generosity score in 2004. The bottom 10% of all state-year observations occur from 2004–2010. This indicates that the generosity growth observed over time is occurring mostly at the lower end of the generosity spectrum.

Only one state, Kansas, ended the period examined with a lower total generosity score in 2016 than in 2004 (approximately 0.36% lower). Although Kansas began ranked 30th in total generosity, it fell to last place, 51st, by 2016. It was also the only state of all 51 states to end with a SNAP generosity score lower than when it began. Fifteen states end with TANF generosity scores lower in 2016 than in 2004, while only four states end with Medicaid scores lower than that with which they began. Most states that have negative percentage changes on any of the three program indices show rather small decreases, less than 10%. However, the TANF index has three outliers: North Dakota's TANF score decreases by 25.82%, Rhode Island's by 17.12%

and Tennessee's by 11.33%. Although all three of these states began ranked in the top 10 in TANF generosity (4th, 9th, and 8th respectively), they fall in the rankings as their scores decreased (to 30th, 33rd and 23rd).

Key Result 2: SNAP Differs in Fundamental Ways From the Other Two Programs

The SNAP index demonstrated a different trend over this period. It showed small but consistent growth from 2004 until a jump from 2008 to 2009; this growth then continued until its peak in 2014, after which it decreased slightly in 2015. The growth curve observed on the SNAP index between 2008 and approximately 2014 is much more dramatic than the more level growth shown by Medicaid and TANF. This leads the second major takeaway from the index results: that SNAP is fundamentally different in some way.

The average percentage change in SNAP generosity between 2008 and 2009 is about 15%, and from 2009 to 2010, it is about 10%, which are much larger than the usual average percentage changes from year to year along other program indices. In addition, TANF shows a large (10%) average percentage change from 2008 to 2009; however, the maximum percentage change that year for any state in TANF generosity is just under 20%, while the maximum change observed in a state along the SNAP index is 60.5%. The time frame for this generosity increase is noteworthy, for it coincides with the Great Recession and large increases in the number of Americans eligible for and applying for SNAP benefits; TANF, by contrast, did not show a similar growth in caseload, likely because of its block grant structure (Rosenbaum, 2013; Slack & Myers, 2014). The federal government pays for 100% of SNAP benefit costs, meaning that states are only responsible for paying about half of the cost of administering the program (FitzGerald, Holcombe, Dahl, & Schwabish, 2012). However, TANF and Medicaid require increased state funding when benefits or eligibility are expanded.

SNAP generosity also shows the most volatility, with percentage change from one year to the next for each state peaking at over 72% for Utah from 2006 to 2007. However, the SNAP index is made up of the fewest indicators, which means that a change in fewer SNAP policies generates much more variation than a change in the same number of policies for TANF or Medicaid. The TANF index is made up of many more indicators; therefore, the large changes in TANF generosity observed from 2008 to 2009 and from 2014 to 2015 beg further scrutiny. When looking at the TANF subindices (Figure 2.7), one can see that the large change in 2009 occurs almost entirely because of an increase in the generosity of behavioral conditions, while the change in 2015 occurs because of a change in benefit limits, although the latter growth is attenuated by a rather sharp decrease the following year. The underlying trends in SNAP applications across the country as the economy reached its nadir might also be responsible for the states' loosening of the rules: when applications surge, so too does the burden placed on the existing program infrastructure. States might well respond to this increased demand by simplifying processes for applying and receiving benefits.

An examination of the five most generous and the five least generous states for each index in each year shows some interesting results. Only 10 states never appear as one of the five most or least generous states in any of the four indices: Arizona, Hawaii, Iowa, Nevada, North Carolina, Ohio, Rhode Island, Vermont, Virginia and West Virginia (see Figures 2.8–2.11). No state that appears within the five most generous states of a particular index in one year also appears among the five least generous for that same program index in another year. This result also means that no state sees a large enough increase or decrease in generosity on any one program to go from being part of the least generous to part of the most generous, or to drop from among the most generous to among the least generous. This result holds true for total generosity as well. However, some states do appear among the most generous states on one program index while also appearing among the least generous on another program index, possibly indicating a substitution of one type of support for another.

Florida, Kentucky, Nebraska, North Dakota, Michigan, New Jersey, South Carolina, and Wisconsin all appear among the five most generous states in at least 1 year on one program index while also appearing among the five least generous states in at least 1 year on another program index. With the exception of North Dakota, which is among the most generous on the TANF index and the least generous on the Medicaid index, one of the indices on which these states all appear among the least or most generous is the SNAP index. This indicates that SNAP generosity might differ from that of the other two programs in some fundamental way. Florida, Kentucky, Michigan, South Carolina, and Wisconsin all appear among the most generous states on the SNAP index at some point, while appearing among the least generous on the TANF or Medicaid indices.

Considering the way that these programs are funded, it is possible that states will substitute towards SNAP generosity when becoming less generous along other programs. Although the options available to states are lesser for modifying SNAP generosity, states do have some flexibility that would allow them to offset contractions in TANF or Medicaid generosity with some increases in SNAP generosity. Some evidence of this flexibility exists in the data: when looking at percentage changes from the prior year (for each program index by state), the correlation of those SNAP percentage changes with Medicaid and with TANF are negative in Florida, Kentucky, and South Carolina. This result means that states that show large or numerous increases on one of these program indices also tend to show large or numerous decreases on the other program index.

However, examining the correlations between the percentage changes by state and correlation between the program indices by state does not necessarily confirm this hypothesis. When looking at percentage changes, SNAP and Medicaid have negatively correlated percentage changes in 26 states, SNAP and TANF have negatively correlated percentage changes in 20 states, and Medicaid and TANF have negatively correlated percentage changes in 22 states. When looking at the program indices themselves, SNAP and Medicaid are negatively correlated in 10 states, SNAP and TANF are negatively correlated in nine states, and Medicaid and TANF are negatively correlated in 13 states.

Key Result 3: A State Can Become More Generous Relative to Itself Over Time While Simultaneously Becoming Less Generous Relative to Other States

Maine began among the most generous states, ranking 3rd in total generosity in 2004 and 4th in 2005 and 2006. In 2007, it fell out of the top five, to 6th, and began to fall steadily. Yet, even as Maine fell in the generosity rankings, for its generosity score was trending mostly upwards (see Figure 2.12). This implies that, even while Maine's generosity score is usually increasing, its drop in the rankings of state generosity is driven less by its decisions to make its own policies less generous than by other states' decisions to make their policies much more generous. Until 2015, Maine's generosity score was usually growing, but it was growing at a much lesser rate than other states. From 2015 to 2016, Maine only fell from 23rd in generosity to 28th; this meant that from 2004 through 2015, Maine fell from 3rd in generosity to 23rd, even as its generosity increased. In fact, Maine's largest drop in the generosity rankings came between 2008 and 2009, when it fell from 8th to 14th even while its score grew from 0.563 to 0.575. Maine, Missouri, North Dakota and South Carolina all fell more than 20 positions in the ranking of states by total generosity, even while their own generosity scores increased; North Dakota fell from 12th to 44th in generosity while its score increased by 1.6%. Missouri fell from 22nd to 46th with a score increase of 8.8% and South Carolina fell from 13th to 34th with a score increase of 13.96%.

Key Result 4: More Generous States Tend to Be in the Northeast and Along the West Coast, While Less Generous States Tend to Be in the South and the (Noncoastal) West

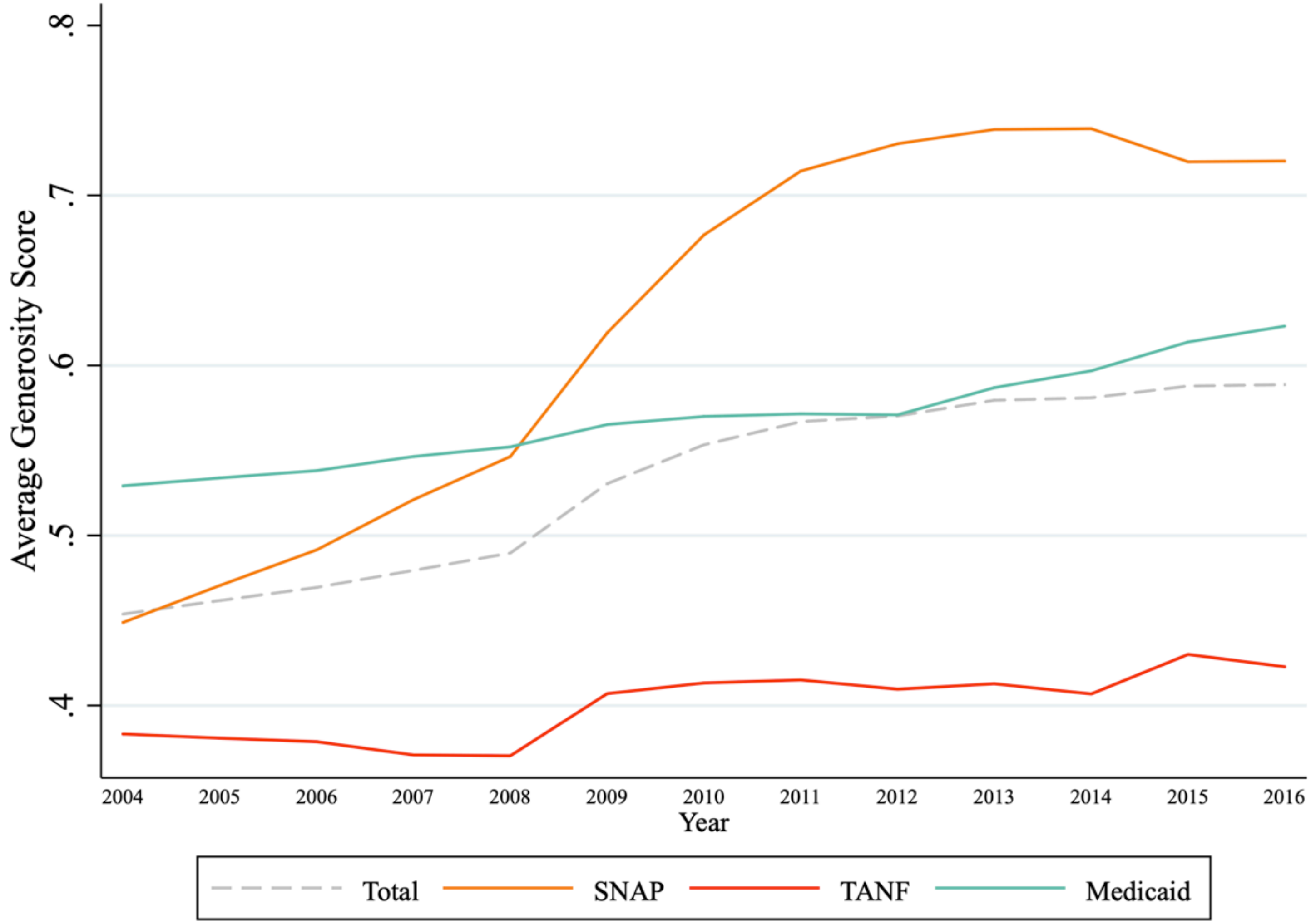
Geographically, the index mostly adheres to expectations. The most generous states tend to be those located in the Northeast and on the West Coast. Southern and "Western" states tend to be less generous, with a number of Midwestern states falling in the middle. Although this is the general trend, there are outliers, especially when looking at the individual program indices. Once again, SNAP seems to show some counter-intuitive results (see Figures 2.15–2.16). Florida, Kentucky, Louisiana, and South Carolina all have observations on the SNAP index that are among the most generous 10%. However, New Hampshire and New Jersey have observations that fall within the least generous 10% of SNAP observations.

Only 20 states ever appear among the five most or least generous states in a given year for only one of the three program indices; however, 11 of those states also appear among the least or most generous states in the total generosity index. These 11 states are evenly divided on which program they scored very high or low, meaning that high or low generosity in the total generosity index is not necessarily driven by a single program more than others.

Three states scored either very high or very low on all four indices. These states are Georgia, which was among the least generous states in at least 1 year for all four indices, and California and New York, which were both among the most generous. New York was among the five most generous states on total generosity in every year examined, while California was similarly generous, although it was not among the five most generous in 2005 and 2006, when it fell to 6th place in total generosity. Georgia, although one of the less generous states, was only among the five least generous states on total generosity in the first 2 years examined, 2004 and 2005. On the SNAP index, neither California nor New York was among the most generous in all years. Both started out on the lower end of SNAP generosity; however, New York jumped from 28th to 4th in SNAP generosity from 2007–2008. California also started out scoring relatively low on the SNAP index (30th in 2004), before beginning to rise in 2011, finally cracking the top five in 2014.

Figure 2.6

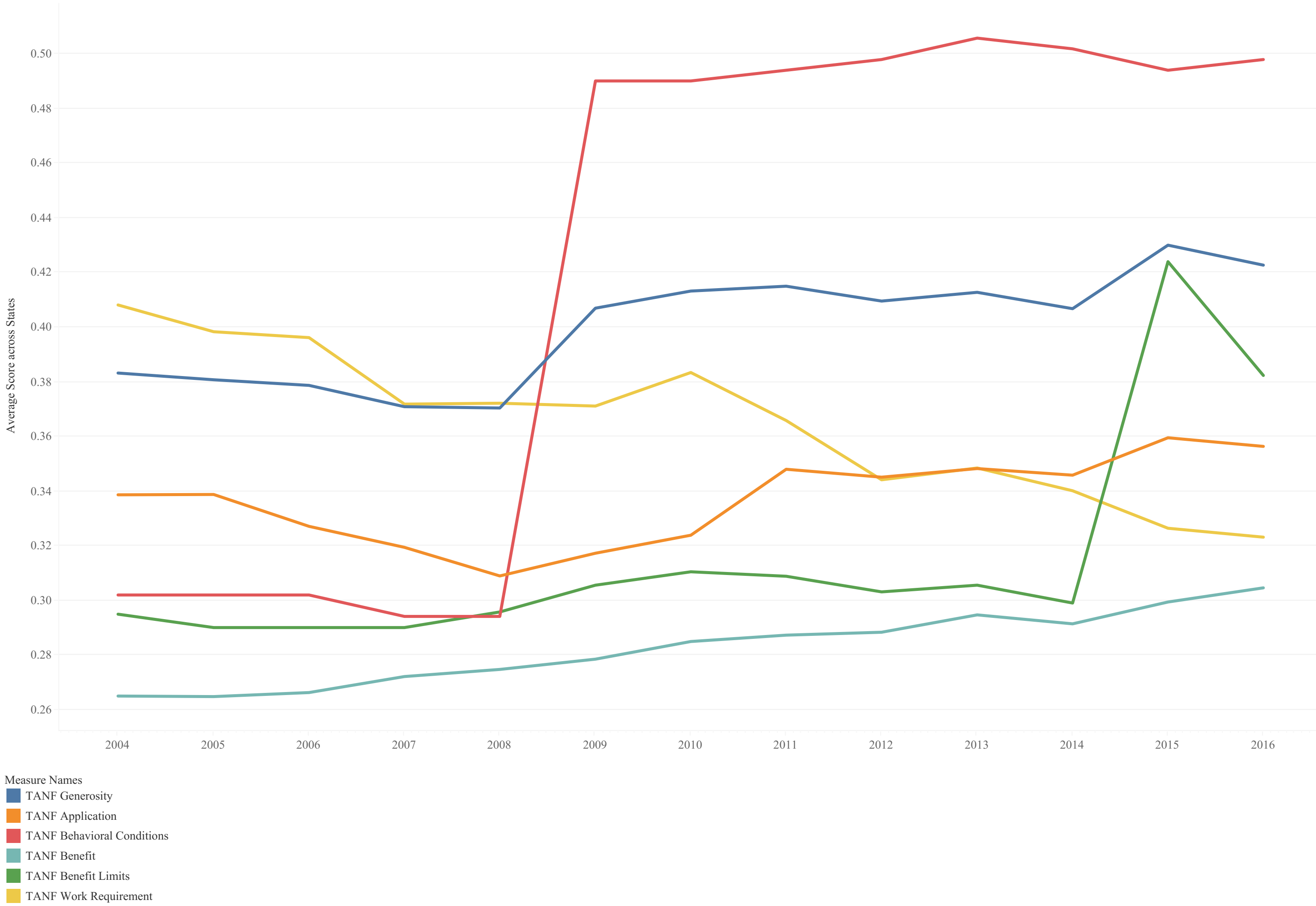
Index Averages Over Time



Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance for Needy Families.

Figure 2.7

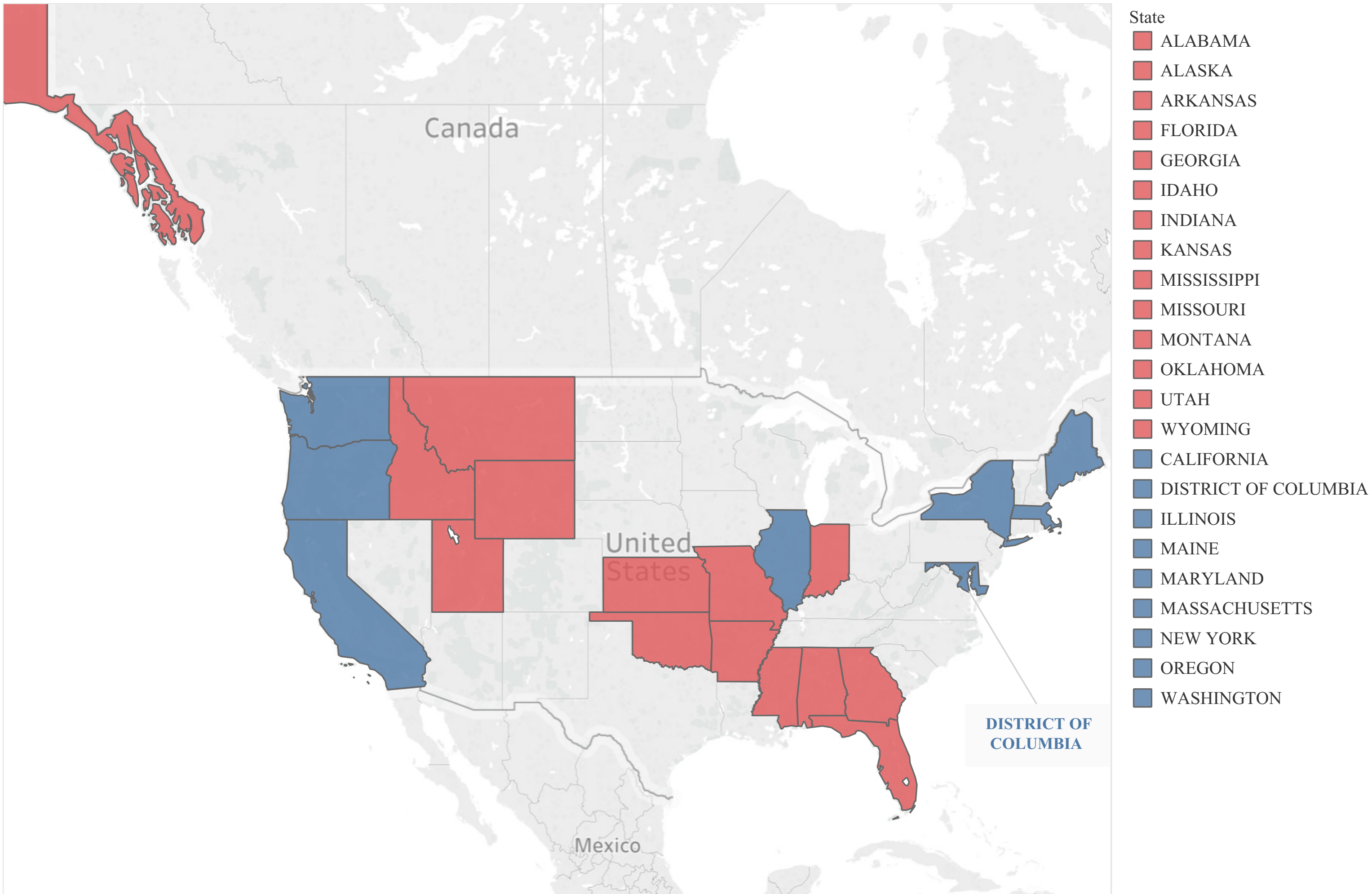
TANF Subindices Over Time



Note. TANF = Temporary Assistance for Needy Families.

Figure 2.8

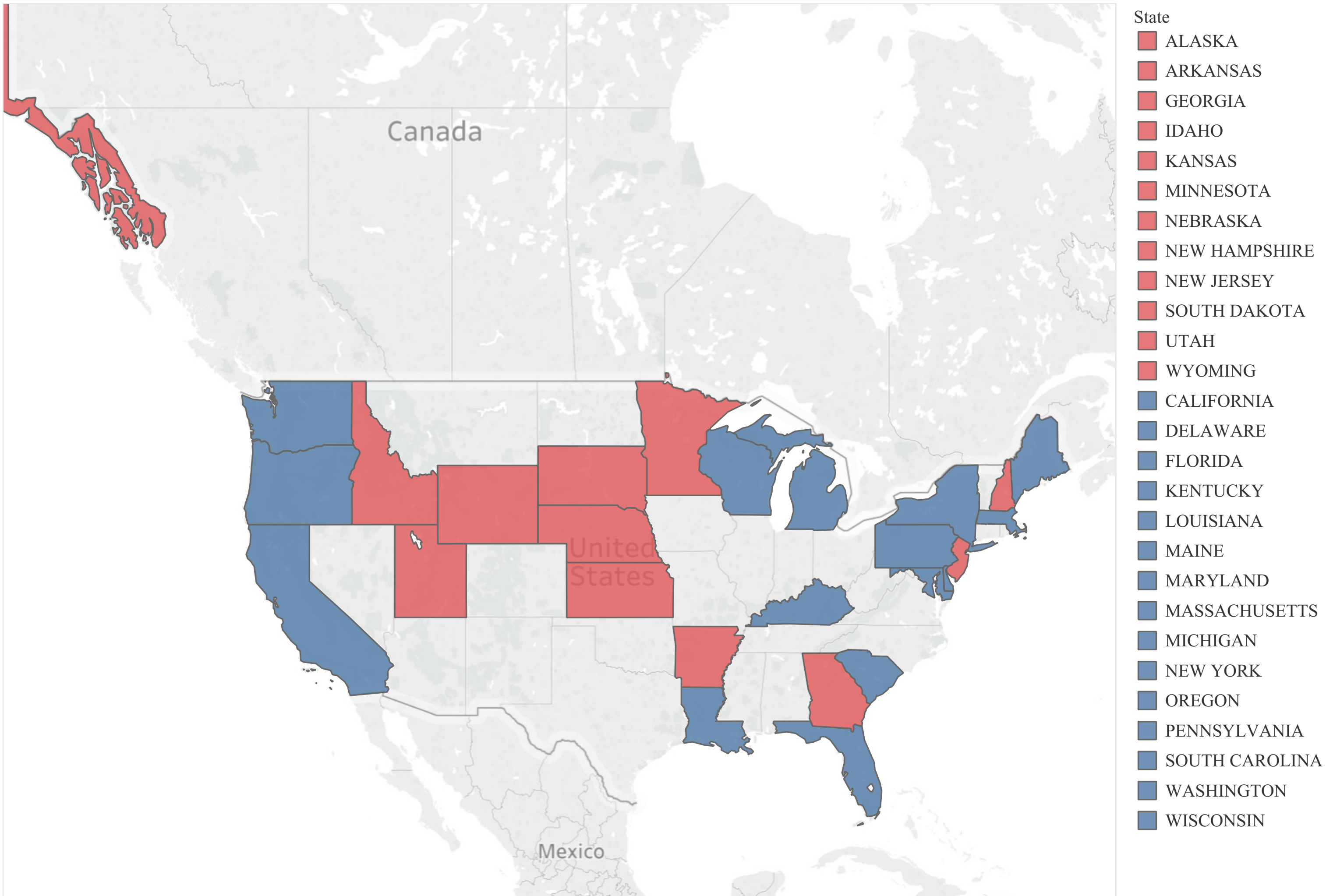
States Appearing Among the Five Most or Least Generous in Any Year, Total Generosity



Note. States that are ever among the least generous appear in red; the most generous appear in blue.

Figure 2.9

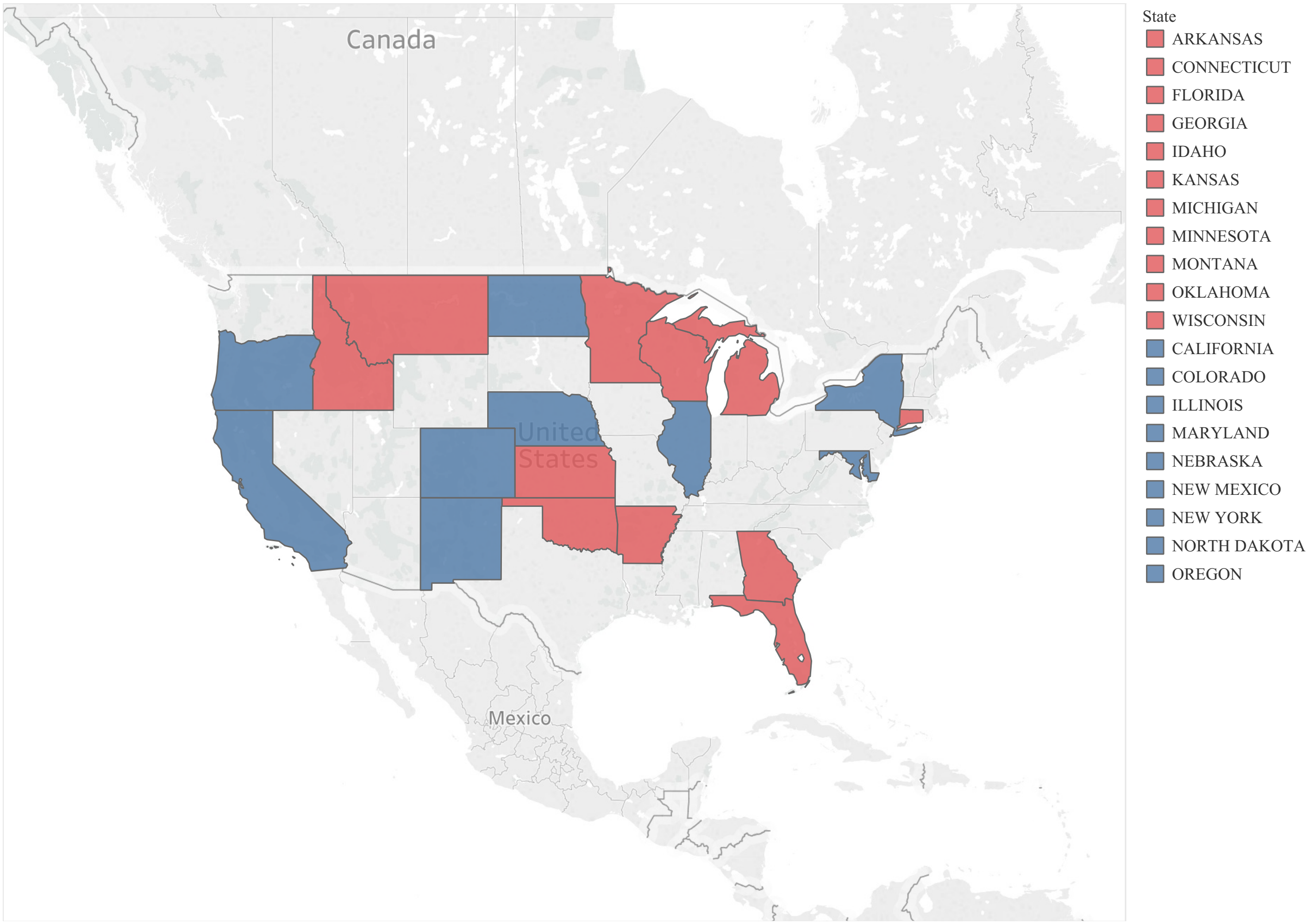
States Appearing Among the Five Most or Least Generous in Any Year, SNAP Generosity



Note. SNAP = Supplemental Nutrition Assistance Program; States that are ever among the least generous appear in red; the most generous appear in blue.

Figure 2.10

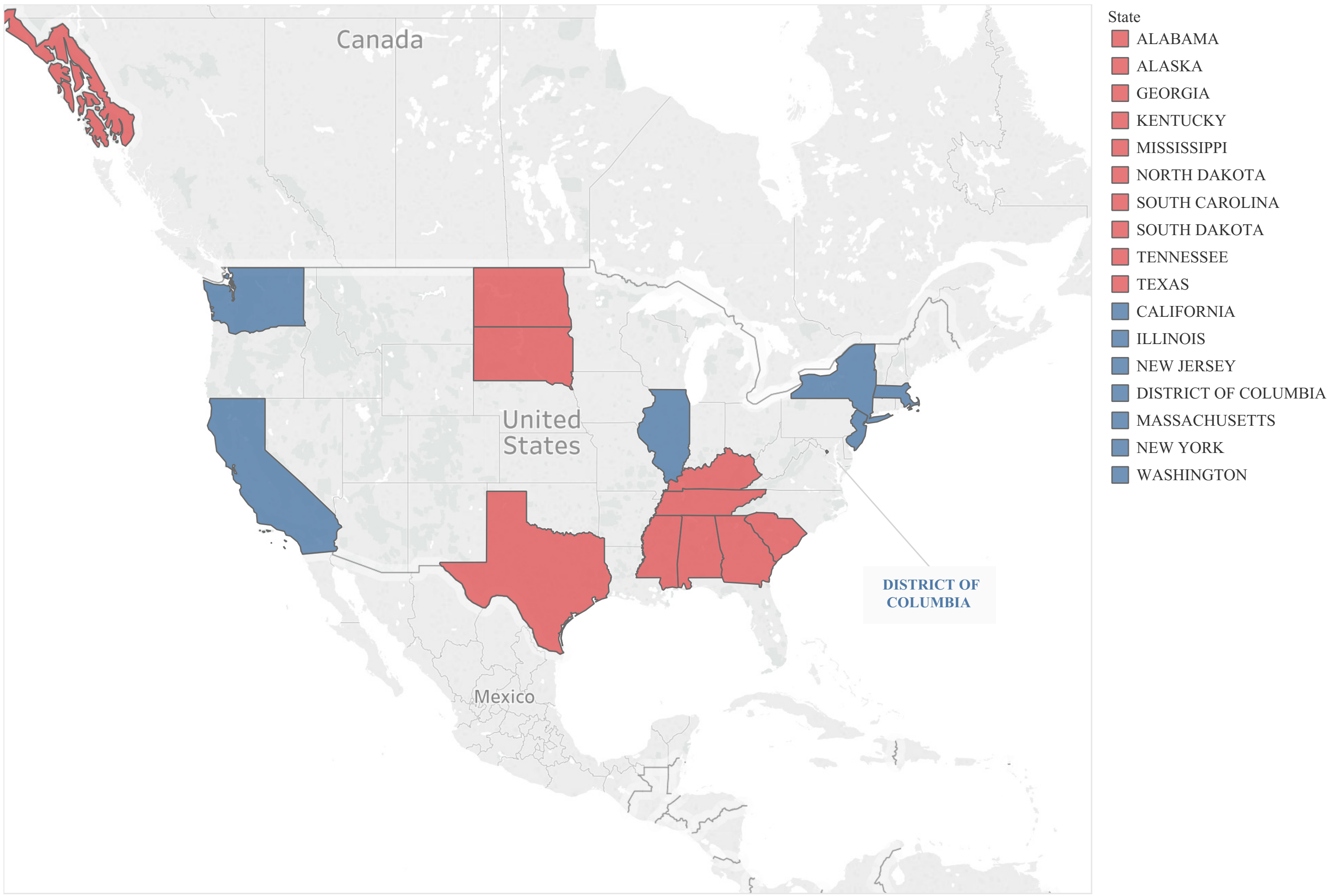
States Appearing Among the Five Most or Least Generous in Any Year, TANF Generosity



Note. TANF = Temporary Assistance for Needy Families. States that are ever among the least generous appear in red; the most generous appear in blue.

Figure 2.11

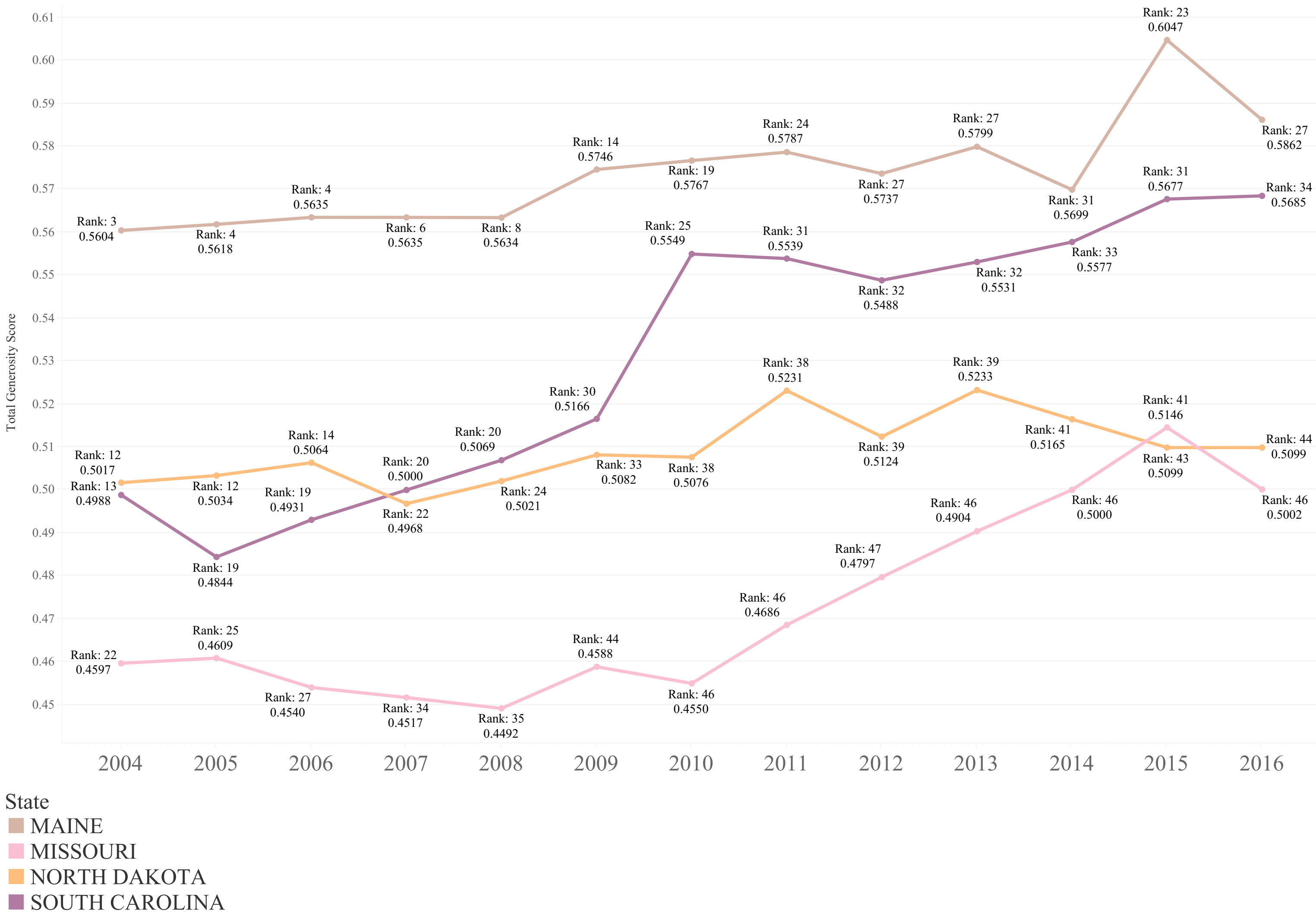
States Appearing Among the Five Most or Least Generous in Any Year, Medicaid Generosity



Note. States that are ever among the least generous appear in red; the most generous appear in blue.

Figure 2.12

Total Generosity Score and Ranking (ME, MO, ND, SC) 2004–2016



Note. ME = Maine, MO = Missouri, ND = North Dakota, SC = South Carolina.

Figure 2.13

Most Generous States in Each Year, 2004–2016

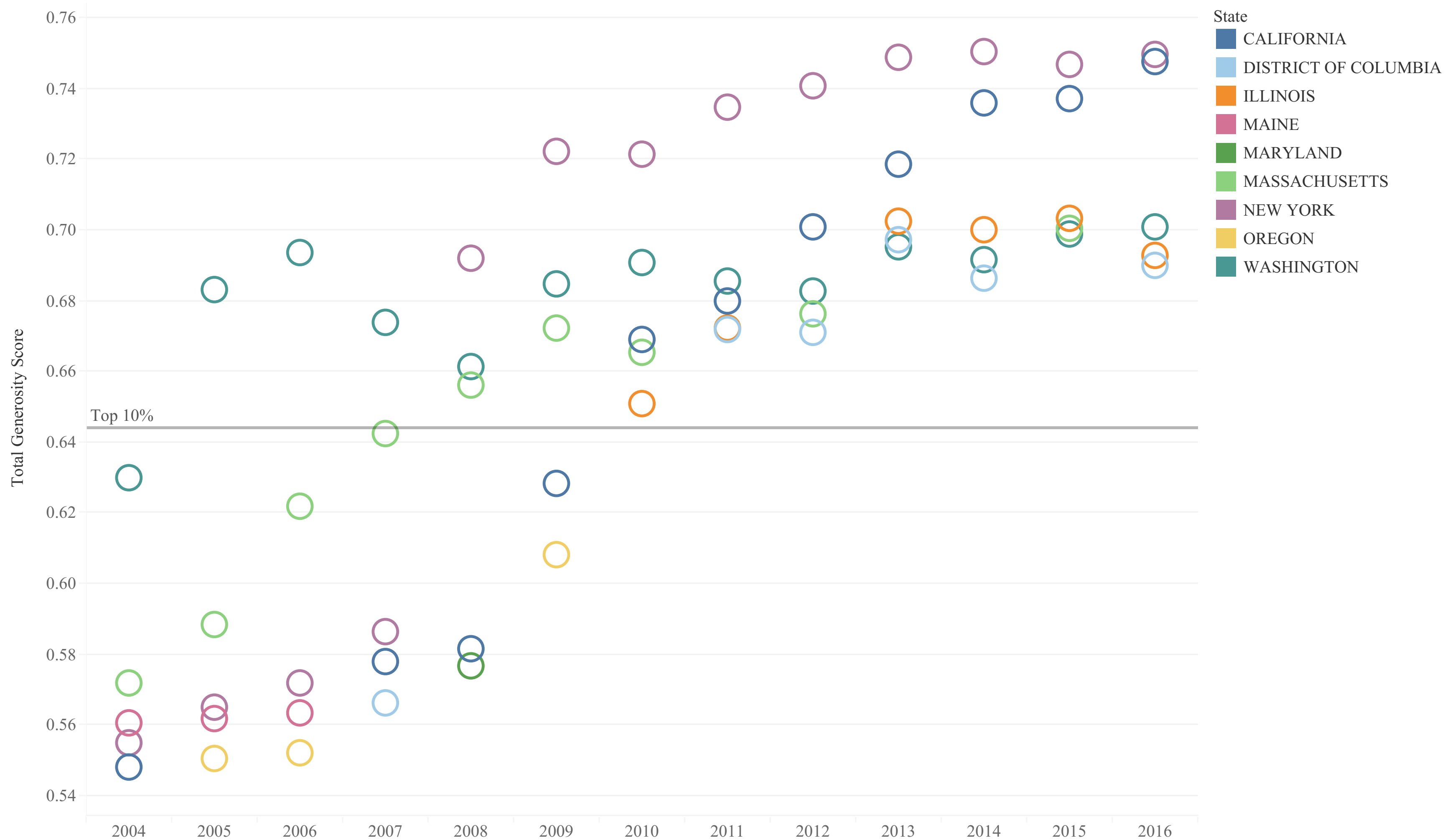


Figure 2.14

Least Generous States in Each Year, 2004–2016

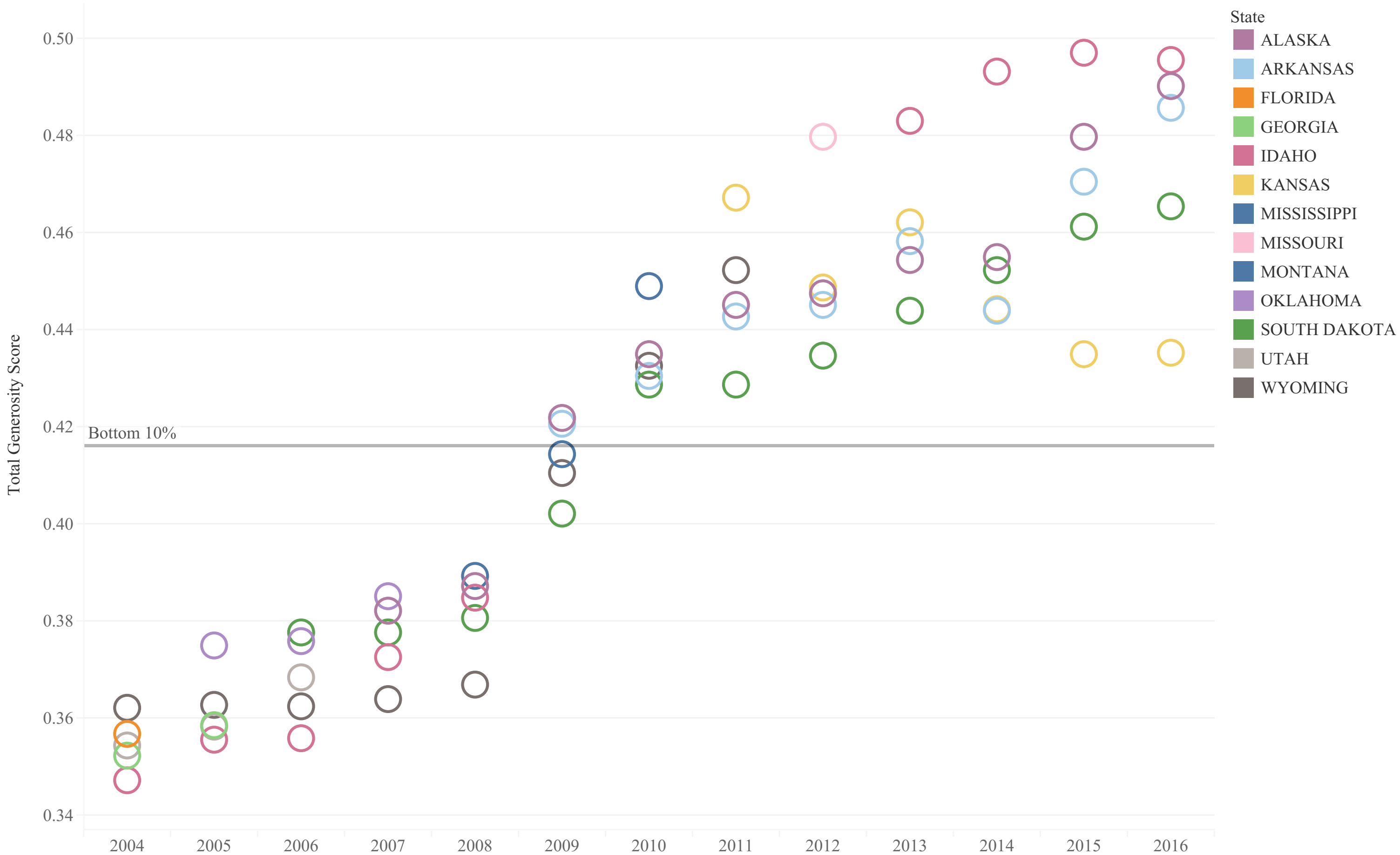
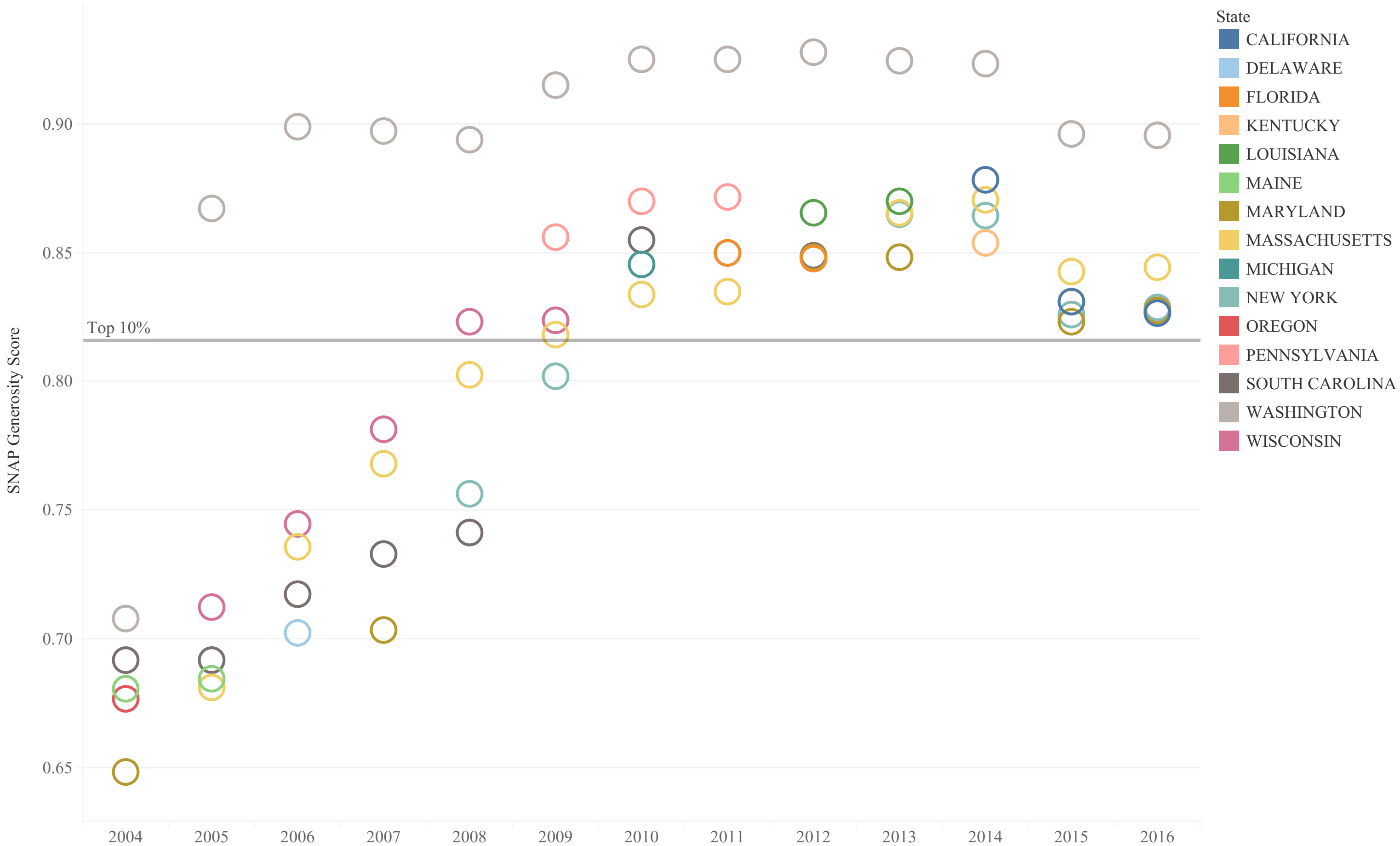


Figure 2.15

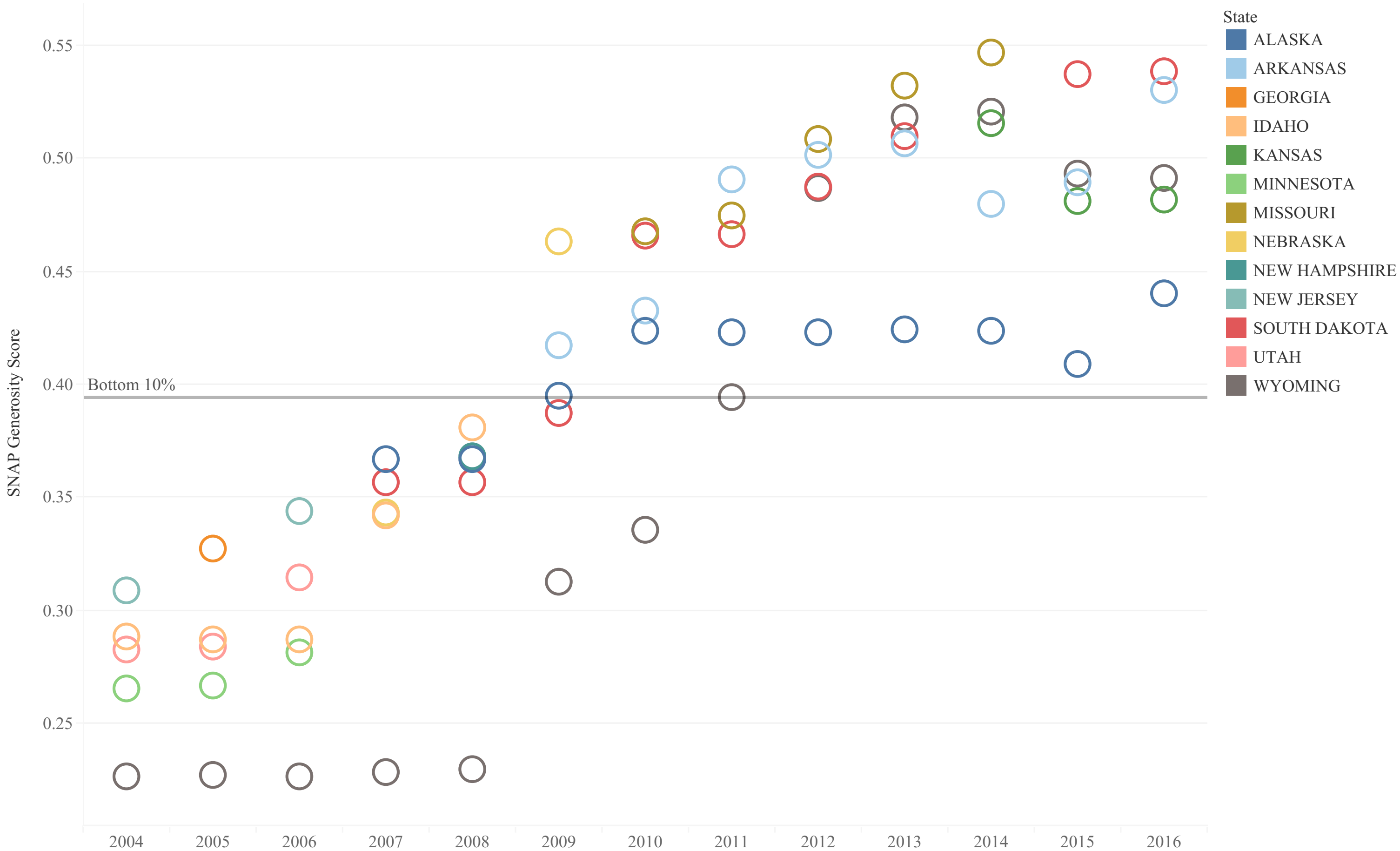
Most Generous (SNAP) States in Each Year, 2004–2016



Note. SNAP = Supplemental Nutrition Assistance Program.

Figure 2.16

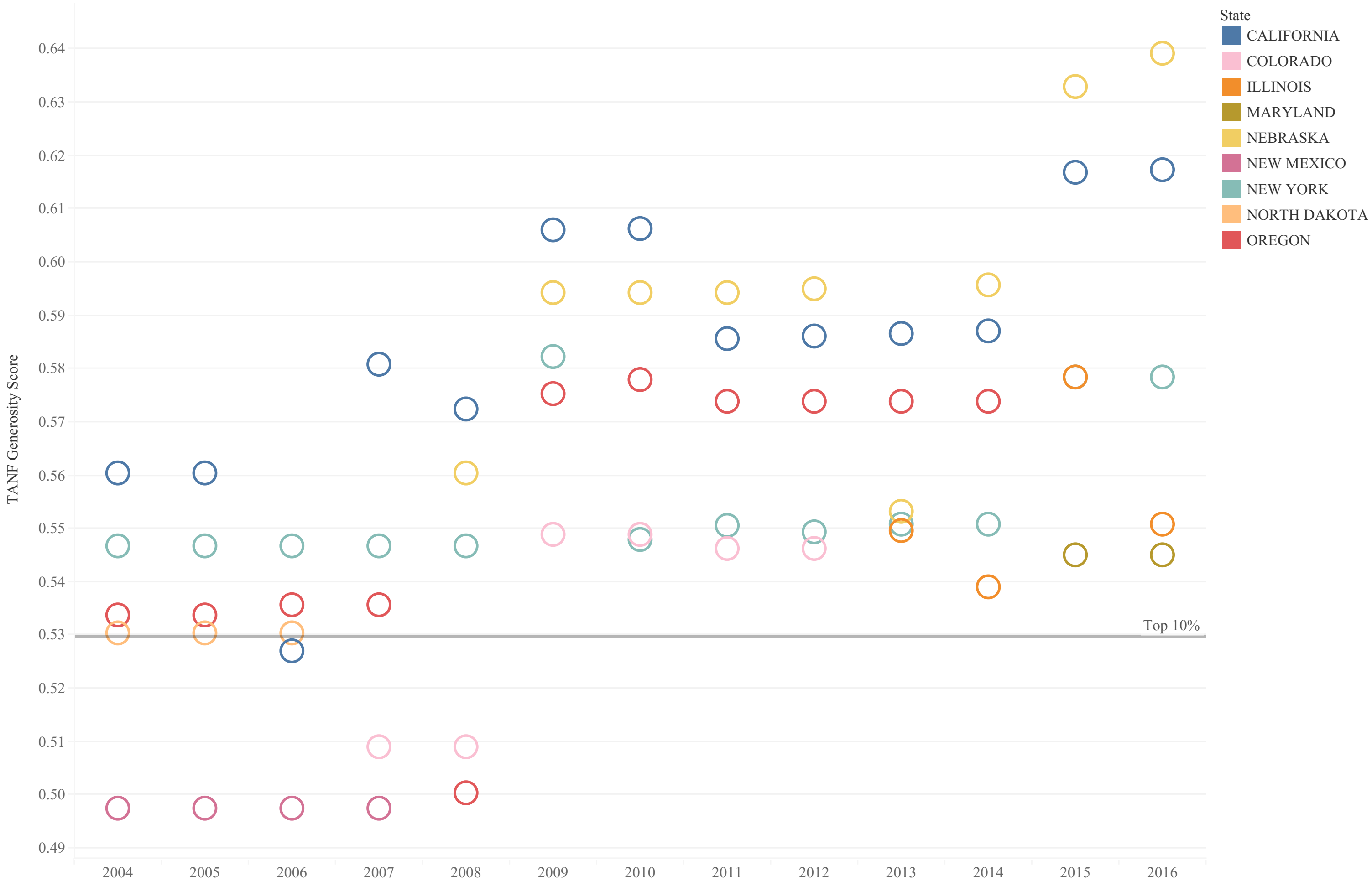
Least Generous (SNAP) States in Each Year, 2004–2016, SNAP Generosity



Note. SNAP = Supplemental Nutrition Assistance Program.

Figure 2.17

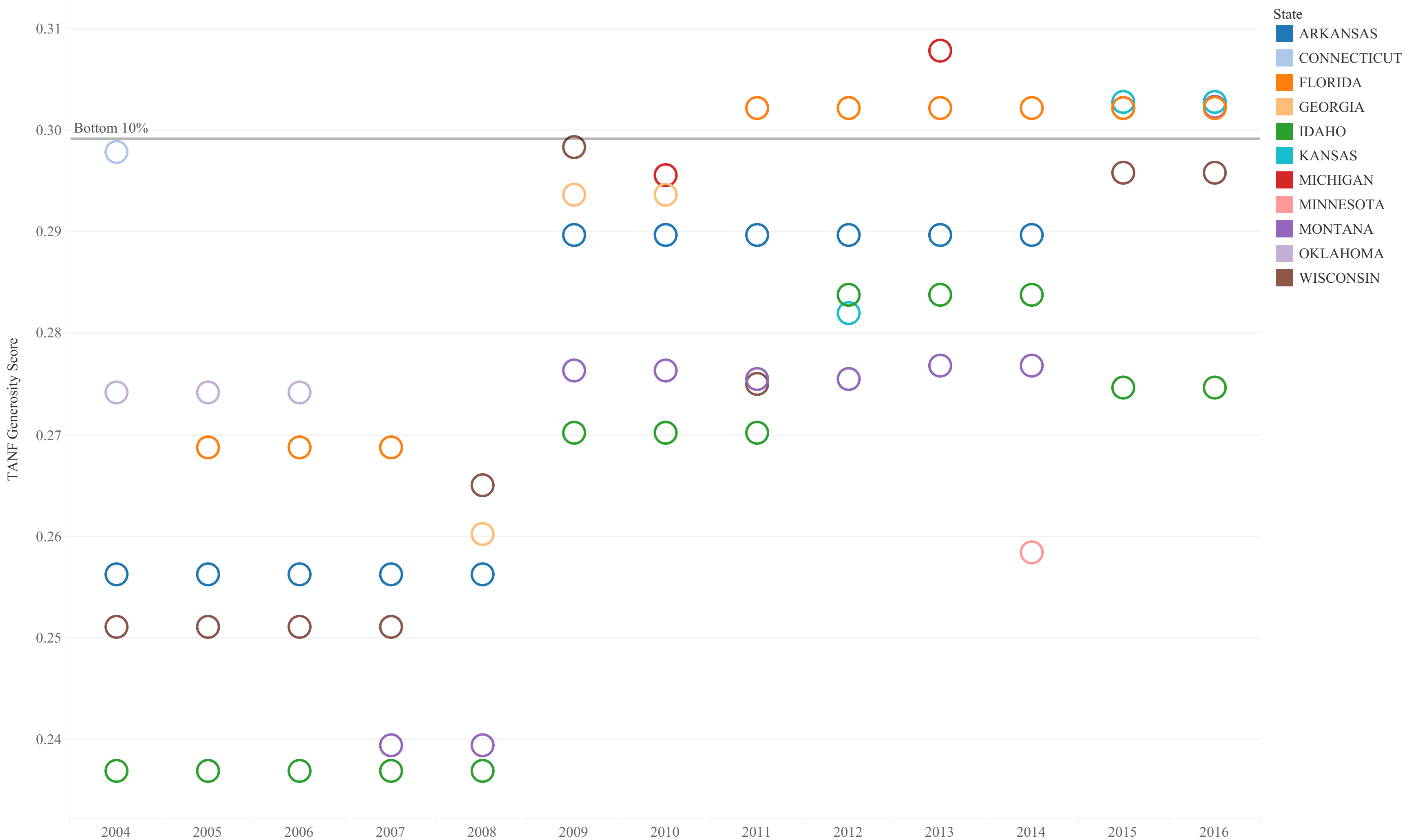
Most Generous (TANF) States in Each Year, 2004–2016



Note. TANF = Temporary Assistance to Needy Families.

Figure 2.18

Least Generous (TANF) States in Each Year, 2004–2016, TANF Generosity



Note. TANF = Temporary Assistance to Needy Families.

Figure 2.19

Most Generous (Medicaid) States in Each Year, 2004–2016

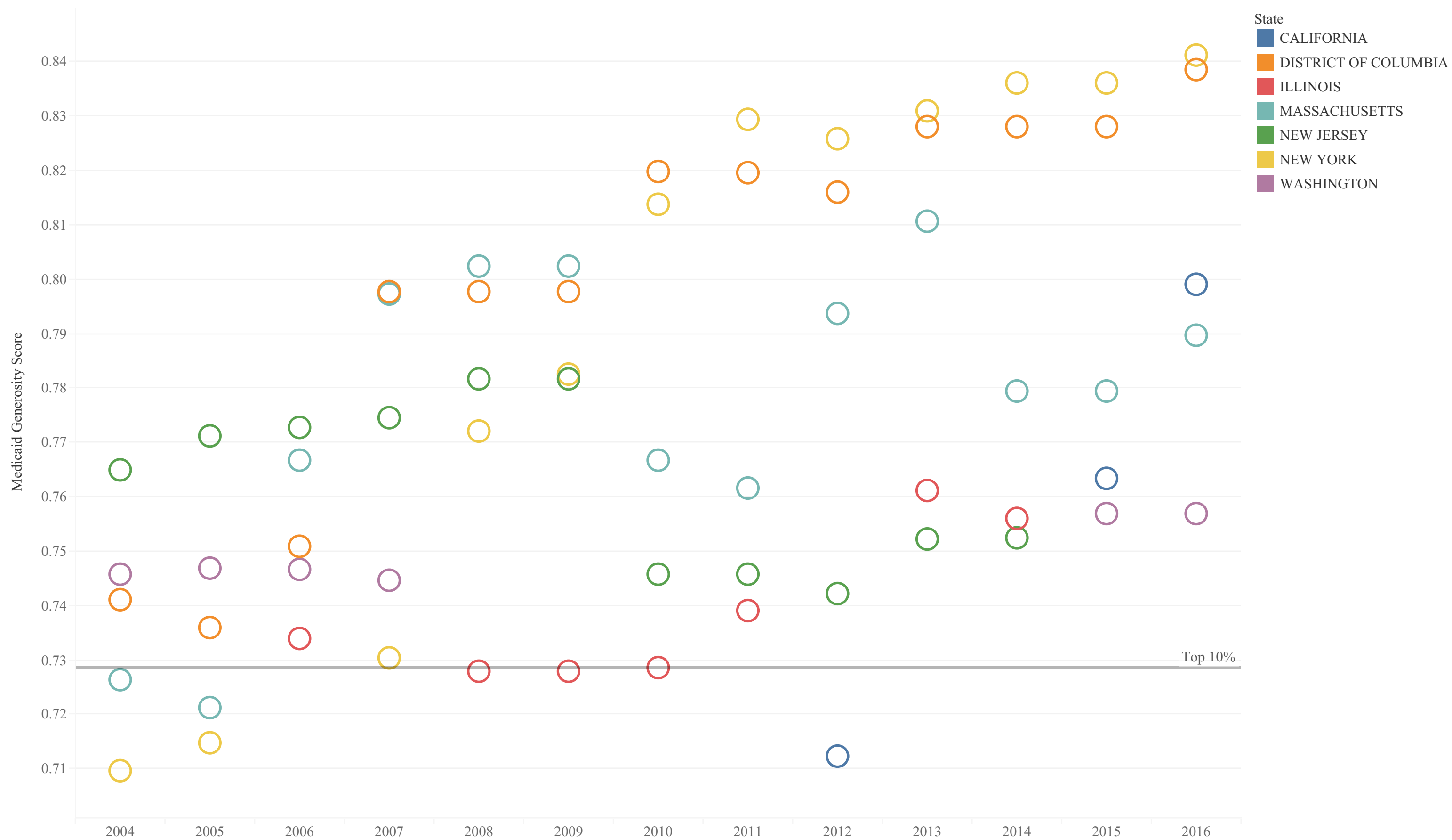


Figure 2.20

Least Generous (Medicaid) States in Each Year, 2004–2016

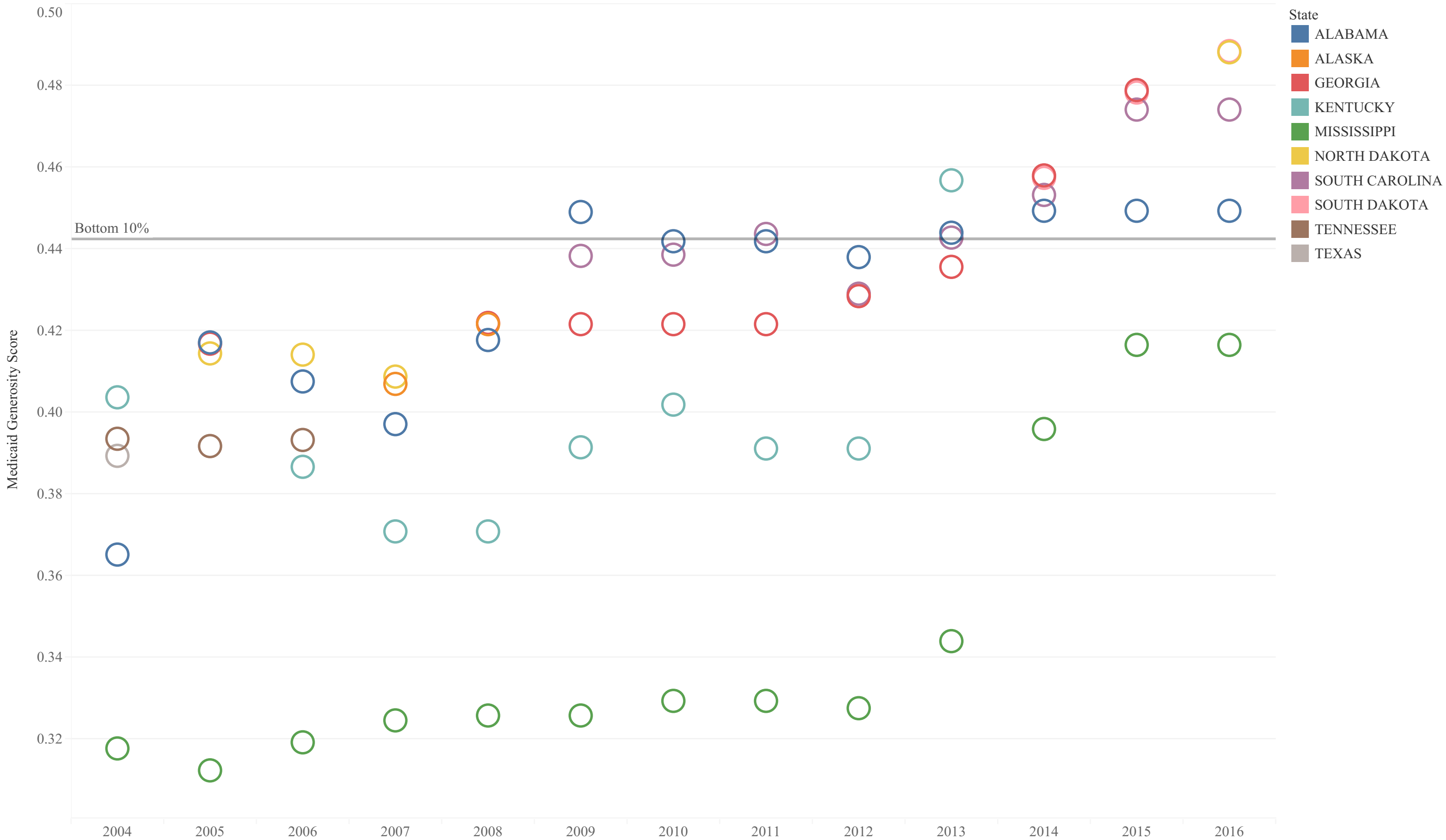


Figure 2.21

California Generosity Scores, 2004–2016

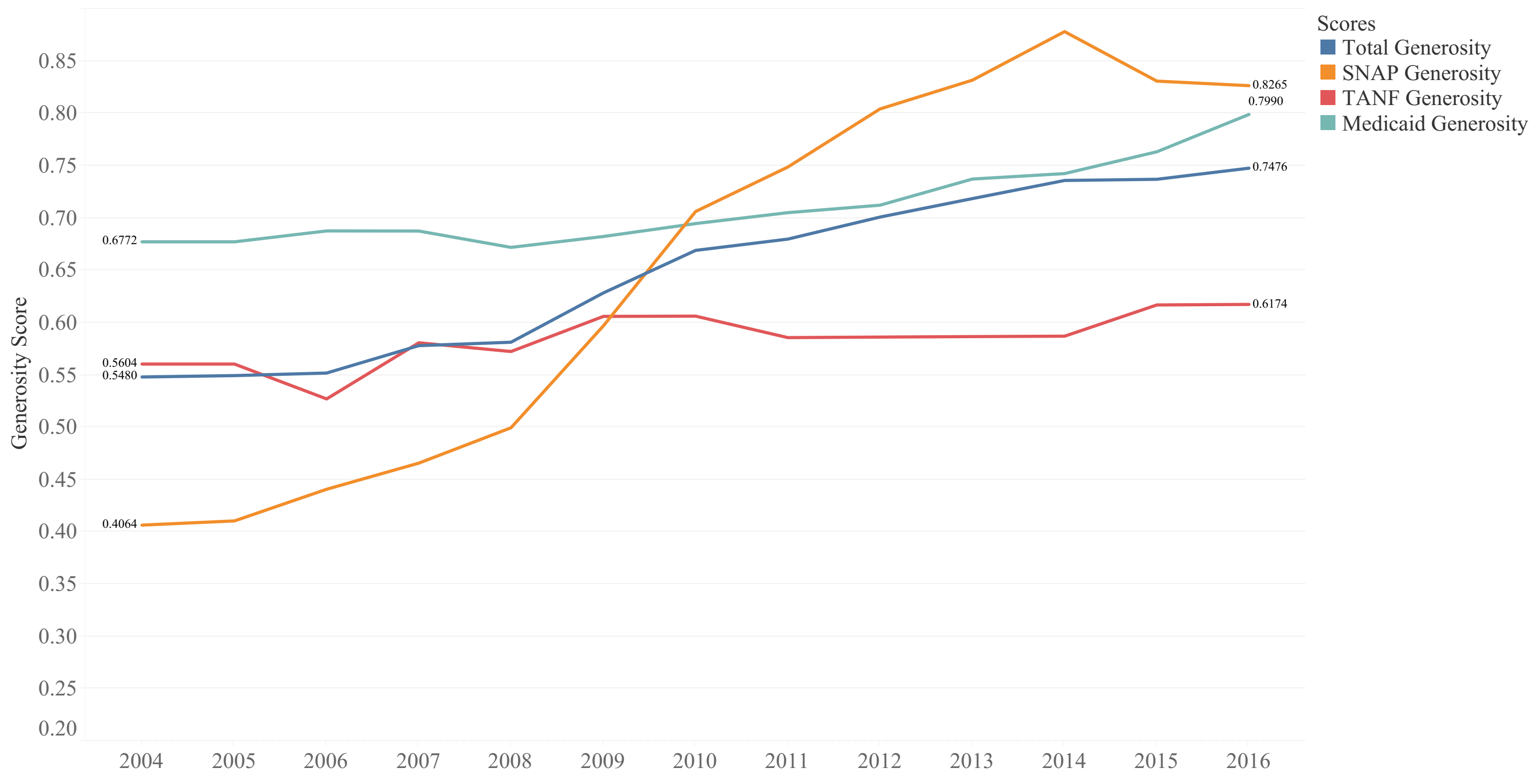


Figure 2.22

New York Generosity Scores, 2004–2016

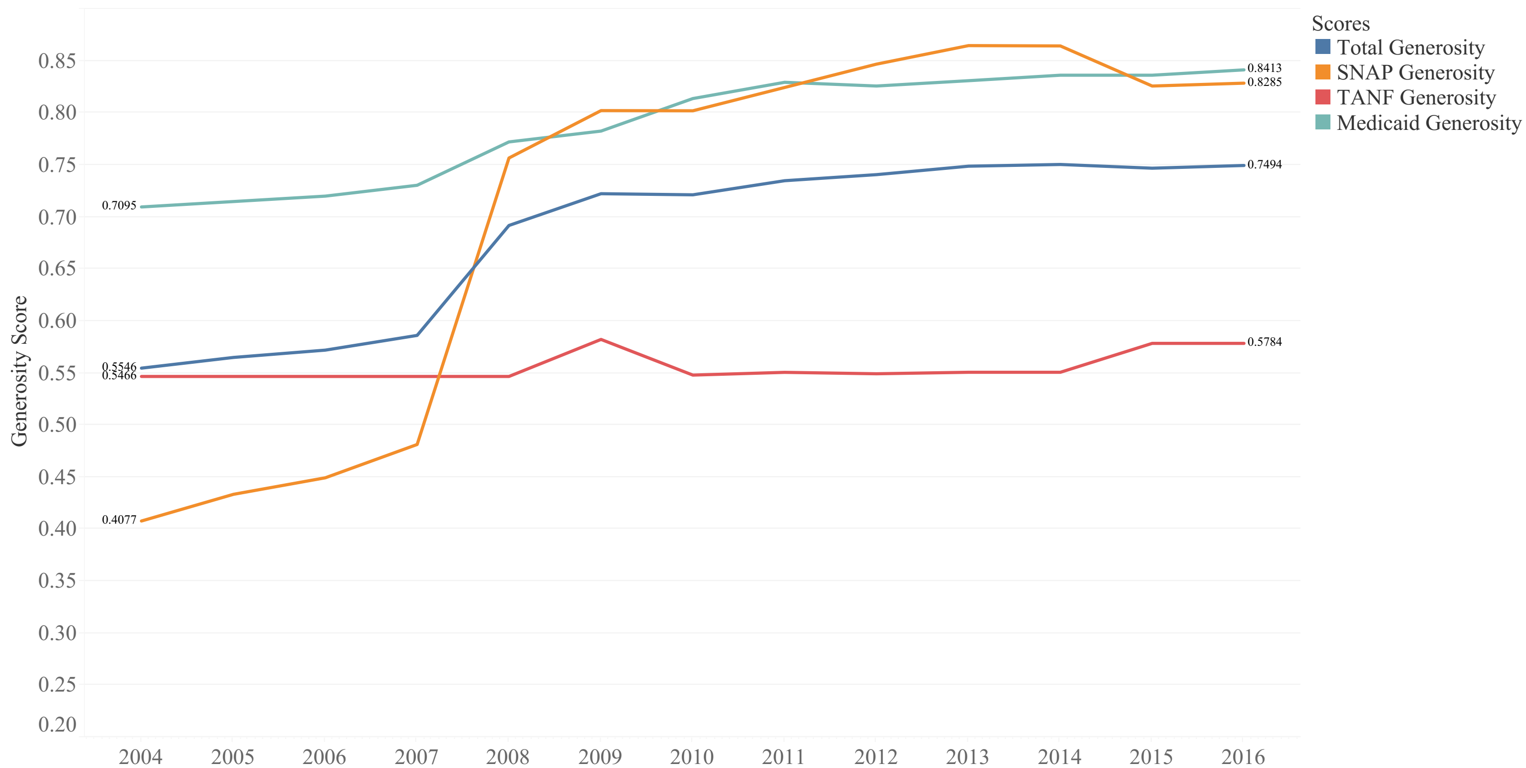


Figure 2.23

Georgia Generosity Scores, 2004–2016

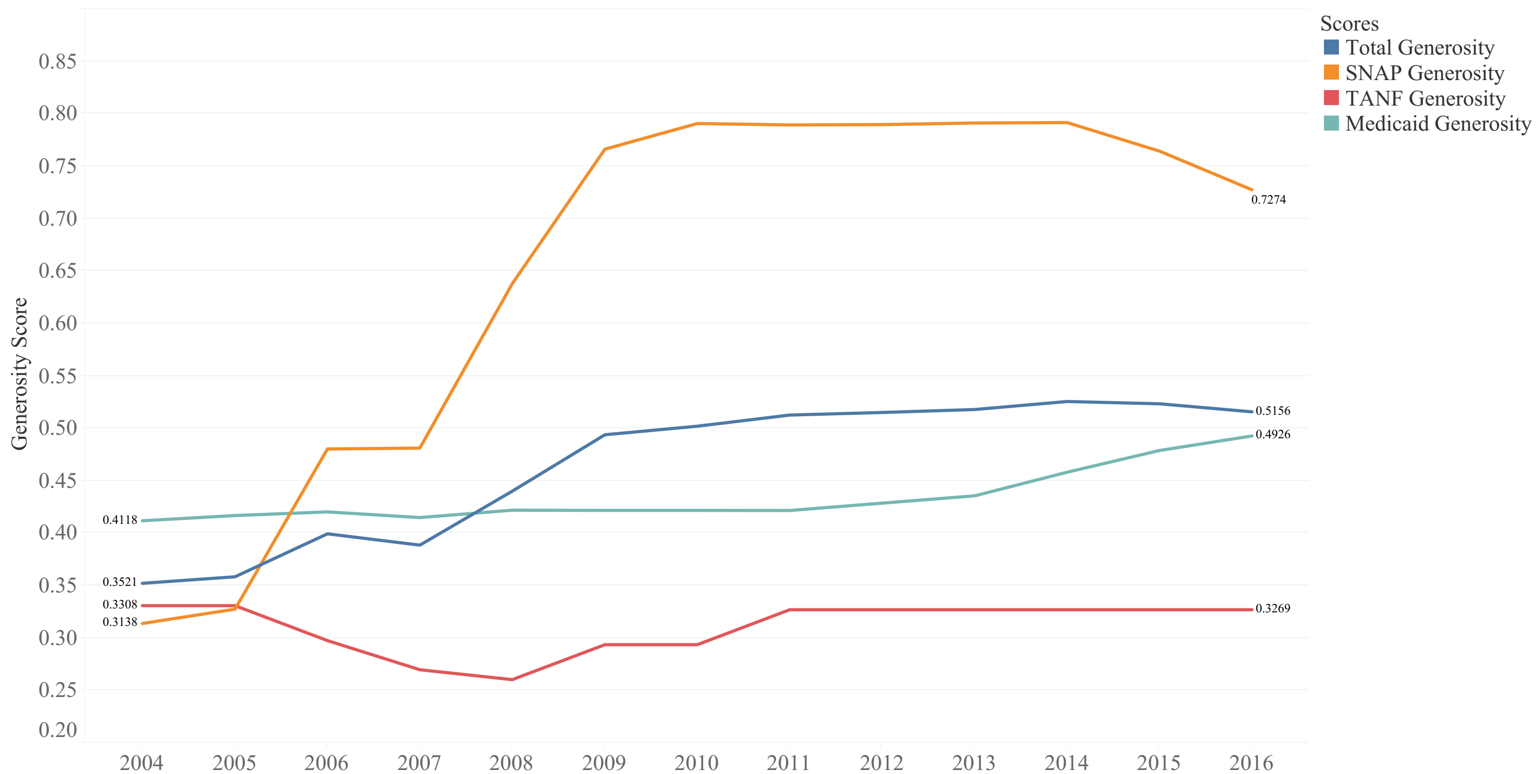
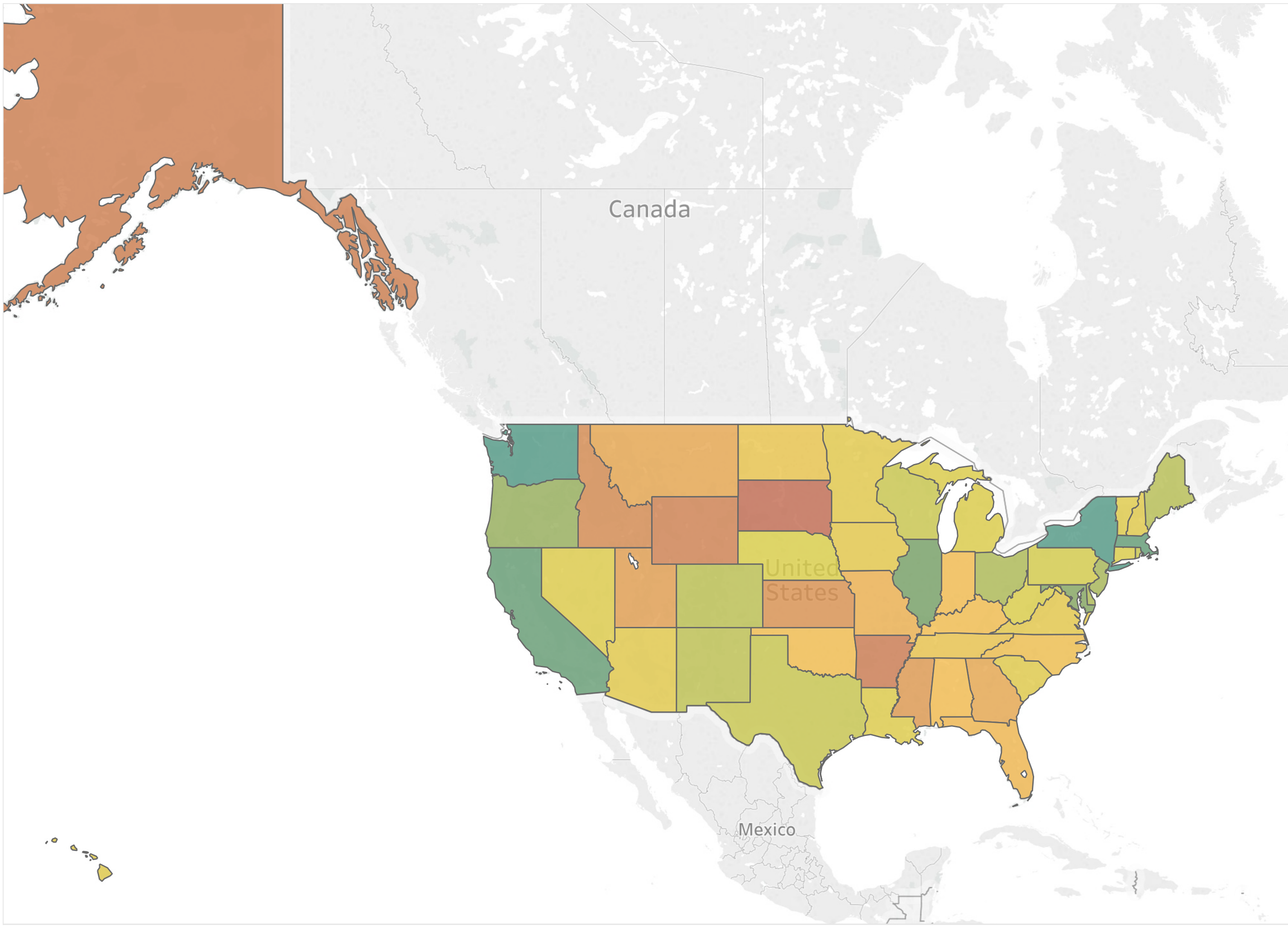


Figure 2.24

Temperature Map, Average Total Generosity



Note. Green indicates higher generosity, while red indicates lower generosity.

Table 2.2

Summary Statistics of Naïve Generosity Indices

Index	Mean	Minimum	Maximum	Standard deviation
Total generosity	.5317172	.3471608	.7503504	.0866135
SNAP	.6259458	.22674	.9276161	.1629048
TANF	.4001061	.2368881	.6392358	.0840427
Medicaid	.5690997	.312247	.8412649	.1087563

Note. $N = 663$. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Table 2.3

Naïve Index Scores by State (2004–2016 average)

State	Generosity	SNAP	TANF	Medicaid
Alabama	.4825094	.5964706	.4227667	.428291
Alaska	.4321277	.3996552	.4176299	.479098
Arizona	.525705	.6667449	.3786946	.5316756
Arkansas	.4287793	.4520999	.2819412	.5522969
California	.6481161	.649694	.5840579	.7105964
Colorado	.5702886	.6024168	.5222792	.5861699
Connecticut	.5442247	.6417972	.3200706	.6708062
Delaware	.5801009	.7481987	.3646922	.6274119
District of Columbia	.6220891	.6291338	.4372067	.7999267
Florida	.4781615	.6674421	.2924904	.4745519
Georgia	.4649217	.6499934	.3106179	.4341538
Hawaii	.5315687	.5624731	.414274	.617959
Idaho	.4408858	.5262875	.2612257	.5351442

State	Generosity	SNAP	TANF	Medicaid
Illinois	.6200768	.6209809	.5070261	.7322234
Indiana	.4819937	.5482592	.3530292	.5446929
Iowa	.5227466	.5961144	.3958146	.5763108
Kansas	.4471332	.5342657	.314449	.4926847
Kentucky	.4832326	.6406651	.3828138	.4262191
Louisiana	.5383711	.6554154	.3744674	.5852305
Maine	.5736161	.7260614	.3899548	.6048322
Maryland	.608059	.7632583	.4588147	.6021039
Massachusetts	.6535289	.7970371	.386859	.7766907
Michigan	.5423533	.713634	.3283918	.5850341
Minnesota	.5264687	.5726395	.3191628	.6876038
Mississippi	.4537161	.6314456	.3847772	.3449256
Missouri	.4725177	.4991187	.3845688	.5338656
Montana	.4642417	.5971961	.2814395	.5140896
Nebraska	.5492888	.490965	.5588428	.5980586
Nevada	.5371904	.6118947	.462956	.5367205
New Hampshire	.528896	.5889559	.4369789	.5607532
New Jersey	.5841934	.6243391	.3674979	.7607434
New Mexico	.5690533	.6330532	.4839889	.5901179
New York	.6833334	.7066482	.5554954	.7878567
North Carolina	.4918579	.61201	.3294165	.5341472
North Dakota	.5093243	.6303724	.4487901	.4488103
Ohio	.5800412	.6808324	.4988356	.5604556

State	Generosity	SNAP	TANF	Medicaid
Oklahoma	.484074	.5921395	.354208	.5058745
Oregon	.5958489	.7088526	.5503352	.5283589
Pennsylvania	.5532521	.7184998	.3587061	.5825504
Rhode Island	.5606193	.6144291	.4110644	.6563645
South Carolina	.5311154	.7855365	.3633202	.4444895
South Dakota	.4159727	.4366546	.3483497	.4629137
Tennessee	.5068779	.589543	.4043062	.5267846
Texas	.5622937	.7048871	.4449366	.5370574
Utah	.4577748	.5289548	.3453239	.4990458
Vermont	.5347096	.6244636	.3933252	.5863401
Virginia	.5217873	.615029	.4803023	.4700305
Washington	.6823975	.881237	.4200994	.7351725
West Virginia	.5455916	.7092323	.3926808	.5348615
Wisconsin	.5607974	.7747017	.2903419	.6173487
Wyoming	.4337517	.3608243	.4357915	.5046391

Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families. All mentions of Washington in these tables refer to Washington state; the city of Washington, D.C. is referred to as District of Columbia.

Table 2.4

Naïve Index Scores by Year (average across 50 states and the District of Columbia)

Year	Generosity	SNAP	TANF	Medicaid
2004	.4537721	.4488554	.3832398	.5292211
2005	.4617495	.470624	.3807759	.5338484
2006	.469468	.4915386	.3787168	.5381487

2007	.4794824	.5210689	.3709164	.5464618
2008	.4896614	.5464439	.3704329	.5521075
2009	.5304693	.6191471	.4069943	.5652663
2010	.5533397	.6767495	.4132604	.5700093
2011	.5669731	.7143335	.4150384	.5715475
2012	.5703178	.7304043	.4095912	.5709579
2013	.5795226	.7388238	.4127933	.5869507
2014	.5809754	.7392619	.4068059	.5968583
2015	.587878	.7197828	.430064	.6137872
2016	.5887142	.7202622	.4227495	.6231309

Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Table 2.5

Naïve Index Leaders

Type of generosity	Ranking	States
Total generosity	Top five states	New York, Washington, Massachusetts, California, District of Columbia
	Bottom five states	South Dakota, Arkansas, Alaska, Wyoming, Idaho
	Largest % change from 2004–2016	Iowa, Oklahoma, Florida, Minnesota, North Carolina
SNAP generosity	Top five states	Washington, Massachusetts, South Carolina, Wisconsin, Maryland
	Bottom five states	Wyoming, Alaska, South Dakota, Arkansas, Nebraska
	Largest % change from 2004–2016	Minnesota, Florida, New Jersey, Rhode Island, Georgia
TANF generosity	Top five states	California, Nebraska, New York, Oregon, Colorado
	Bottom five states	Idaho, Montana, Arkansas, Wisconsin, Florida
	Largest % change from 2004–2016	Oklahoma, Wyoming, District of Columbia, Delaware, Nebraska
Medicaid generosity	Top five states	District of Columbia, New York, Massachusetts, New Jersey, Washington
	Bottom five states	Mississippi, Kentucky, Alabama, Georgia, South Carolina
	Largest % change from 2004–2016	Texas, Tennessee, Oregon, West Virginia, Ohio

Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Section 2.5 Scale Results

The results of the individual program models would indicate that there is not some underlying factor inherent to the program that drives the generosity of that program's indicators for both TANF and Medicaid; however, SNAP does show some degree of an underlying latent generosity. This echoes the results of the naïve index, where the SNAP program index differed from the other two program indices in its pattern of growth as well as in which states could be considered leaders and laggards in SNAP generosity. The variables included in the SNAP index (see Table 2.6) are also all positively correlated with underlying SNAP generosity, which indicates that all the indicators move in tandem with the latent construct; there is no tradeoff in generosity within the SNAP indicators.

The TANF program analysis (see Table 2.7) seems to indicate that a latent TANF generosity does not exist in the same way. Only nine out of more than 20 variables remained significant indicators of this generosity. Two of those nine indicators—those measuring coverage of immigrants and behavioral conditions placed on recipients—are negatively related to TANF generosity, indicating possible tradeoffs in different areas of the program. Looking at the R^2 values also seems to indicate that the real generosity being measured stems from the diversion program as well as time limits on receipt.

TANF diversions are a way in which states attempt to reduce the numbers on their welfare rolls. By providing a one-time payment to households experiencing a short-term crisis, states hope to keep that household from having to receive traditional TANF assistance in the future (London, 2003; Ridzi & London, 2006). The time limits refer to both lifetime limits as well as intermittent or spell limits. The other variables that remain significant enough for inclusion in the model have small coefficients as well as small R^2 values. This would seem to indicate that there is something about diversion and time limits—both of which serve to keep the number of households on the welfare rolls smaller—that change together.

The Medicaid single program analysis (see Table 2.8) also has indicators that are negatively related to the latent Medicaid generosity. These are indicators that address copays for services covered in every state. The most significant indicators of Medicaid generosity seem to be those that address eligibility, both related to income as well as to immigration status.

However, model fit statistics indicate that the model overall is not a good fit, showing that latent Medicaid generosity (as a construct) does not exist according to all the available indicators.

When one looks at the results of the intermediate latent variables for the coverage model by breadth versus depth, one can see that these two latent constructs cannot accurately account for the variation in generosity. The breadth construct went from 24 indicators to 15, however the model was a poor fit (see Table 2.9). Nevertheless, although not perfectly explaining underlying breadth of coverage, the indicators with the largest factor loadings and R^2 values were in fact the variables that indicated which persons would be eligible for coverage. The finding is noteworthy that, although Medicaid coverage indicators about the asset and income limits of applicants remained significant, the asset tests and income limits of TANF applicants and recipients either were excluded from the model or had very little explanatory power. Although the means tests for SNAP are federally determined, SNAP does allow states that use BBCE to extend eligibility to people eligible for alternative programs such as TANF or Medicaid, which have income and asset limits that vary by state. Whether states allowed BBCE remained an important indicator of breadth of coverage.

These results would indicate that whatever latent breadth of coverage generosity that exists to explain which persons would be eligible for these programs works differently for TANF. It seems that latent generosity does not significantly influence asset and income limits for TANF, but rather the latent generosity affects the categorical eligibility determinations. The types of people or households that are eligible for TANF are the indicators remaining in the model, most significantly whether immigrants would be eligible beyond the eligibility mandated in federal law (in fact, coverage of immigrants in all three programs are highly important in breadth of coverage generosity).

Nevertheless, the model of latent generosity of the depth of coverage in these programs seems to be a poor conceptualization of any latent construct. A number of the indicators that seem to measure the depth of benefits are negatively correlated, especially across programs. Latent generosity of depth as initially conceived included a number of indicators for regulations or procedures that make it relatively easier or more difficult to comply with program administration and so to continue to receive benefits. These indicators included TANF work requirements, or whether an applicant would need to have a face-to-face interview to certify their income. These indicators are perhaps more properly thought of as manifesting a different type of generosity which was part of the third model, that of administrative burden, rather than depth.

This third model contrasted latent generosity of the burden of administering or navigating the program (of the regulations and procedures facing both clients and workers) with the latent generosity of the rest of the program, namely the benefits that participants receive, and which persons would be eligible. Once again, this model seems to differ by program. The model constructing latent generosity of the administrative burden (where more generosity would indicate fewer regulations, easier procedures, etc.) is not a particularly good fit (see Table 2.10). A review of the results of this model indicates that the administration of SNAP is highly explanatory, while that of TANF not only fails to explain much if any of this latent generosity, but in fact shows the existence of a diversion program that seems to indicate more generosity for this latent variable.

That a diversion program is correlated with this particular latent concept of generosity is understandable, since the administrative burden being measured is not only client facing, but is also an indication of the burden put on employees who are responsible for administering the program. Although a diversion from TANF was determined to be less generous because its goal would be to keep welfare rolls smaller, the ability for workers to divert households instead of having to open a case is a reduction in administrative load.

The final hypothesized intermediate latent variable was that affecting the nonadministrative parts of the programs, which I characterized as representing the generosity of actual benefits as well as the generosity of eligibility for the program. Much like the latent generosity of the depth of these programs, there was no real correlation between the selected indicators. The fact that so many of the hypothesized models were ill fitting or failed to converge is telling. Although I might hypothesize a latent generosity that influences the ways in which policies and regulations change in these programs, such a construct does not exist across all three programs. When the indicators for all programs were combined into joint models, no indication was found that any underlying factor affected them jointly. Even within individual programs there does not appear to exist an underlying latent generosity, for only SNAP showed any real promise as a program model.

After failing to confirm any of the hypothesized models, I attempted to pare down the indicators included according to these failed models. Ultimately, I found that smaller cross-sections of indicators could be thought of as clustering together (e.g., the indicators surrounding asset tests). The elimination of the SNAP asset test through BBCE has recently come under fire by the Trump administration (Newman, 2019). Looking at the indicators dealing with asset tests, I found that there is likely some latent factor affecting states' policies towards asset tests (see Table 2.11). This model included indicators for whether a state used BBCE; what its applicant and recipient asset limits are for TANF; and whether it eliminated asset limits for Medicaid, for parents, or for all recipients. Although all of the factor loadings were significant ($p < 0.05$), the R^2 values for the SNAP BBCE and the TANF recipient asset limit were not at all significant and the TANF applicant asset limit was significant only at the 0.10 level ($p = 0.078$). It seems that whether a state had eliminated any asset tests for Medicaid was the true indication of this underlying asset test generosity, but that underlying generosity did also have some influence on how a state choose to set its asset tests for the other two programs.

Finally, a model containing only three indicators (one for each program) was constructed to determine whether the coverage that states provide to noncitizens was driven by an underlying latent factor (e.g., perhaps a prevailing attitude towards immigration). I found that some underlying construct does exist and that it influences all three programs in a similar way to a similar degree (see Table 2.12). This model is perfectly identified; therefore, it does not contain any statistics regarding model fit; however, all three, factor loadings are highly significant, as are all three R^2 values. Whatever is the underlying trait affecting access to the social safety net for noncitizens, it equally affects their access to SNAP, TANF, and Medicaid.

Table 2.6

Single Factor Results for Latent SNAP Generosity

Indicator	Standardized factor loading	R^2	Model fit information	
FS01	0.764 (0.027)	0.584 (0.041)	X^2	207.302
FS02	0.556 (0.041)	0.309 (0.045)	*P* value	0.0000
FS03	0.359 (0.036)	0.129 (0.026)	RMSEA	0.052
FS04	0.878 (0.019)	0.772 (0.034)	Probability RMSEA <= .05	0.325
FS05	0.883 (0.019)	0.780 (0.034)	CFI	0.991
FS06	0.853 (0.030)	0.728 (0.051)	TLI	0.989
FS07	0.324 (0.041)	0.105 (0.027)	SRMR	0.073
FS08	0.248 (0.028)	0.062 (0.014)		
FS09	0.393 (0.032)	0.155 (0.025)		
FS10	0.719 (0.029)	0.517 (0.042)	Measurement error correlations	
FS12	0.875 (0.018)	0.765 (0.032)	FS02 with FS09	0.346 (0.048)
FS13	0.456 (0.042)	0.208 (0.039)	FS04 with FS05	0.857 (0.033)
FS14	0.560 (0.036)	0.314 (0.040)	FS06 with FS07	0.571 (0.078)

Note: CFI = Comparative fit index; FS =Food Stamps; RMSEA = Root mean square error of approximation; SNAP = Supplemental Nutrition Assistance Program; SRMR = Standardized root mean square residual. Standard errors are given in parentheses underneath estimates. All coefficients are statistically significant at the $p < 0.05$ level unless marked with an asterisk.

Table 2.7

Single Factor Results for Latent TANF Generosity

Indicator	Standardized factor loading	R^2	Model fit information	
TANFD3	0.819 (0.011)	0.670 (0.019)	X^2	297.510
TANFD5	0.963 (0.014)	0.928 (0.027)	*P* value	0.0000
TANFD6	0.925 (0.016)	0.855 (0.030)	RMSEA	0.112
TANFL3	0.374 (0.066)	0.140 (0.050)	Probability RMSEA <= .05	0.000
TANFTEEN	0.114 (0.056)	0.013 (0.013)	CFI	0.960
TANFF1	0.060 (0.049)	0.004 (0.006)	TLI	0.942
TANFL1	0.483 (0.043)	0.233 (0.042)	SRMR	0.108
TANFBV0	-0.230 (0.035)	0.053 (0.016)		
TANFIM0	-0.141 (0.048)	0.020 (0.014)		
			Measurement error correlations	
			TANFBV0 with TANFF1	-0.407 (0.039)
			TANFL1 with TANFF1	0.541 (0.061)

Note. CFI = Comparative fit index; RMSEA = Root mean square error of approximation; SRMR = Standardized root mean square residual; TANF = Temporary Aid to Needy Families; TLI = Tucker-Lewis index.

Table 2.8

Single Factor Results for Latent Medicaid Generosity

Indicator	Standardized factor loading	R^2	Model fit information	
MCEL01	0.693 (0.028)	0.481 (0.038)	X^2	632.949
MCEL04	0.667 (0.021)	0.444 (0.027)	*P* value	0.0000
MCEL05	0.619 (0.030)	0.383 (0.038)	RMSEA	0.072
MCEL06	0.567 (0.031)	0.321 (0.035)	Probability RMSEA <= .05	0.000
MCAD01	0.239 (0.039)	0.057 (0.018)	CFI	0.758
MCAD03	0.425 (0.049)	0.181 (0.042)	TLI	0.712
MCAD04	0.697 (0.051)	0.486 (0.071)	SRMR	0.117
MCAD05	0.411 (0.039)	0.169 (0.032)		
MCAD06	0.478 (0.044)	0.229 (0.042)		
MCAD07	0.093 (0.046)	0.009* (0.009)	Measurement error correlations	
MCAD09	0.460 (0.058)	0.212 (0.053)	MCAD05 with MCAD03	0.590 (0.050)
MCAD11	0.186 (0.032)	0.035 (0.012)	MCAD07 with MCAD06	0.719 (0.049)
MCAD12	0.249 (0.031)	0.062 (0.015)	MCAD12 with MCAD11	0.624 (0.020)
MCIM99	0.684 (0.028)	0.468 (0.039)	MCMANDCO with MCBOPAV	-0.512 (0.027)
MCBOPAV	0.173 (0.039)	0.030 (0.014)	MCMANDCO with MCRX	0.559 (0.038)
MCMANDCO	-0.257 (0.036)	0.066 (0.019)		
MCRX	-0.093 (0.061)	0.009* (0.011)		

Note. CFI = Comparative fit index; MC = Medicaid; RMSEA = Root mean square error of approximation; SRMR = Standardized root mean square residual; TLI = Tucker-Lewis index.

Table 2.9

Single Factor Results for Latent Breadth Generosity

Indicator	Standardized factor loading	R^2	Model fit information	
FS01	0.436 (0.036)	0.190 (0.031)	X^2	521.194
FS08	0.453 (0.029)	0.205 (0.026)	*P* value	0.0000
FS13	0.550 (0.037)	0.302 (0.041)	RMSEA	0.076
TANFPREG	0.290 (0.047)	0.084 (0.027)	Probability RMSEA <= .05	0.000
TANFINC1	0.188 (0.039)	0.035 (0.015)	CFI	0.816
TANF2PAR	0.230 (0.040)	0.053 (0.019)	TLI	0.776
TANFIM0	0.509 (0.037)	0.259 (0.038)	SRMR	0.091
MCEL01	0.663 (0.026)	0.439 (0.035)		
MCEL03	0.639 (0.027)	0.408 (0.034)		
MCEL04	0.723 (0.017)	0.522 (0.025)	Measurement Error Correlations	
MCEL05	0.692 (0.024)	0.478 (0.033)	TANFIM0 with TANFINC1	0.383 (0.040)
MCEL06	0.499 (0.037)	0.249 (0.037)	MCEL03 with MCEL01	0.974 (0.002)
MCAD04	0.619 (0.055)	0.383 (0.068)	MCAD05 with TANFINC1	-0.366 (0.042)
MCAD05	0.337 (0.040)	0.114 (0.027)	MCAD04 with TANF2PAR	-0.745 (0.126)
MCIM99	0.732 (0.025)	0.536 (0.036)		

Note. CFI = Comparative fit index; FS =Food Stamps; MC = Medicaid; RMSEA = Root mean square error of approximation; SRMR = Standardized root mean square residual; TLI = Tucker-Lewis index.

Table 2.10

Single Factor Results for Latent Administrative Burden Generosity

Indicator	Standardized factor loading	R^2	Model fit information	
FS01	0.719 (0.028)	0.517 (0.040)	X^2	1027.512
FS02	0.555 (0.039)	0.308 (0.043)	*P* value	0.0000
FS04	0.982 (0.009)	0.964 (0.017)	RMSEA	0.077
FS05	0.977 (0.010)	0.955 (0.020)	Probability RMSEA<=.05	0.000
FS06	0.807 (0.026)	0.652 (0.043)	CFI	0.946
FS09	0.449 (0.030)	0.202 (0.027)	TLI	0.939
FS10	0.673 (0.031)	0.453 (0.041)	SRMR	0.113
FS12	0.849 (0.019)	0.720 (0.041)		
FS13	0.404 (0.042)	0.163 (0.034)		
TANFD1	-0.185 (0.045)	0.034 (0.017)	Measurement error correlations	
TANFBV0	0.353 (0.031)	0.125 (0.022)	MCAD10 with MCAD09	0.704 (0.074)
MCAD01	0.152 (0.039)	0.023 (0.012)	MCAD12 with MCAD11	0.618 (0.020)
MCAD04	0.206 (0.053)	0.042* (0.022)		
MCAD05	0.351 (0.041)	0.123 (0.029)		
MCAD06	0.241 (0.047)	0.058 (0.023)		
MCAD08	0.205 (0.041)	0.042 (0.017)		
MCAD09	0.273 (0.079)	0.074* (0.043)		
MCAD10	0.462 (0.050)	0.214 (0.046)		
MCAD11	0.263 (0.034)	0.069 (0.018)		
MCAD12	0.222 (0.032)	0.049 (0.014)		

Note. CFI = Comparative fit index; FS = Food Stamps; MC = Medicaid; RMSEA = Root mean square error of approximation; SRMR = Standardized root mean square residual; TLI = Tucker-Lewis index.

Table 2.11

Single Factor Results for Latent Generosity of Asset Tests

Indicator	Standardized factor loading	R^2	Model fit information	
FS01	0.167 (0.059)	0.028* (0.20)	X^2	17.355
TANFA1	0.200 (0.057)	0.040 (0.023)	*P* value	0.0016
TANFA4	0.147 (0.051)	0.022* (0.015)	RMSEA	0.062
MCAD04	0.675 (0.128)	0.456 (0.173)	Probability RMSEA<=.05	0.215
MCAD05	0.805 (0.164)	0.648 (0.263)	CFI	0.998
			TLI	0.996
			SRMR	0.039

Measurement error correlations	
TANFA1 with TANFA4	0.848 (0.010)

Note. CFI = Comparative fit index; FS = Food Stamps; MC = Medicaid; RMSEA = Root mean square error of approximation; SRMR = Standardized root mean square residual; TLI = Tucker-Lewis index.

* Although not significant at $p < 0.05$ level, this value is significant at the $p < 0.10$ level.

Table 2.12

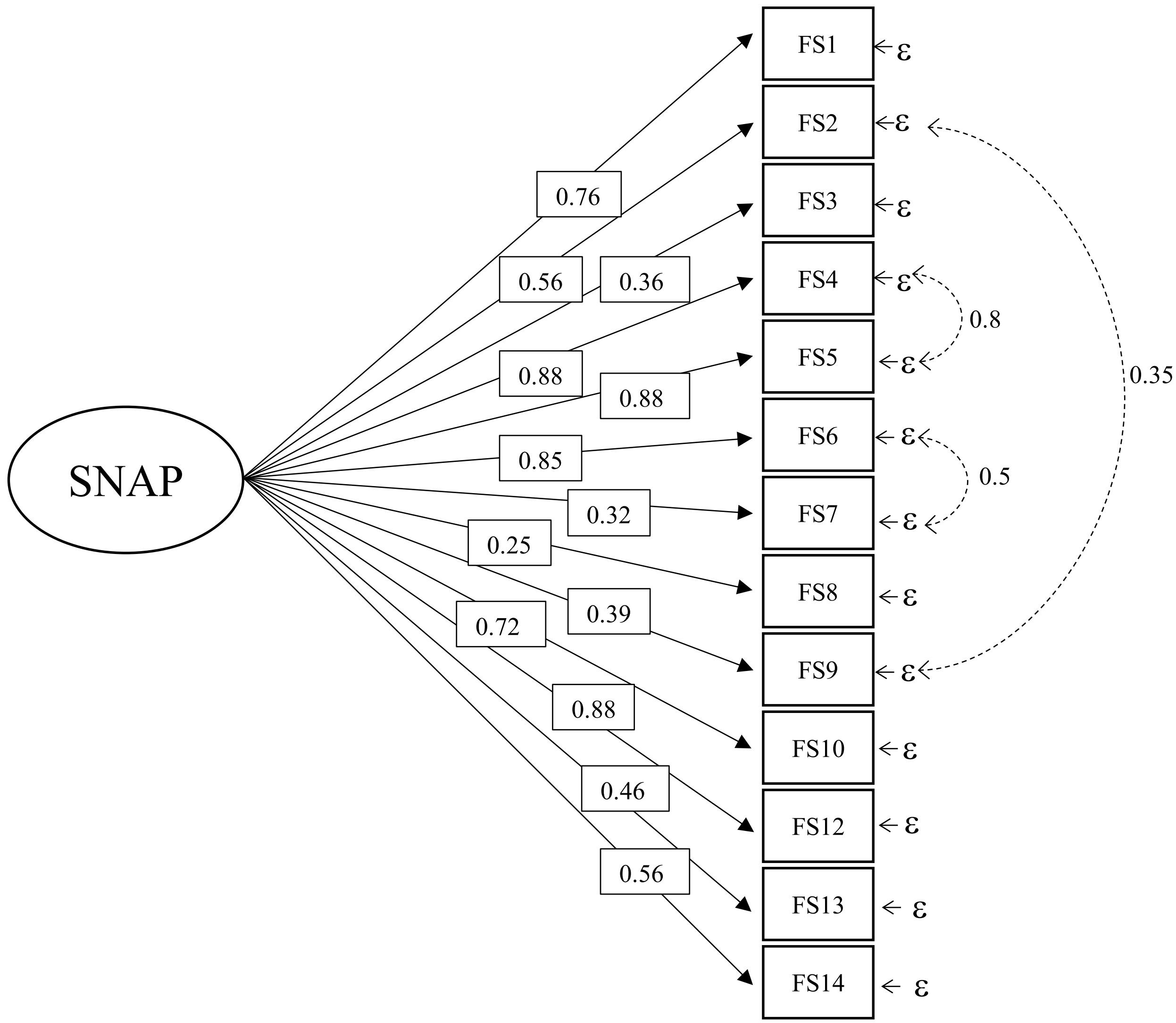
Single Factor Results for Latent Generosity to Noncitizens

Indicator	Standardized factor loading	R^2
FS08	0.685 (0.09)	0.469 (0.054)
TANFIM0	0.631 (0.035)	0.398 (0.044)
MCIM99	0.666 (0.037)	0.443 (0.049)

Note. FS = Food Stamps; MC = Medicaid; TANF = Temporary Assistance to Needy Families.

Figure 2.25

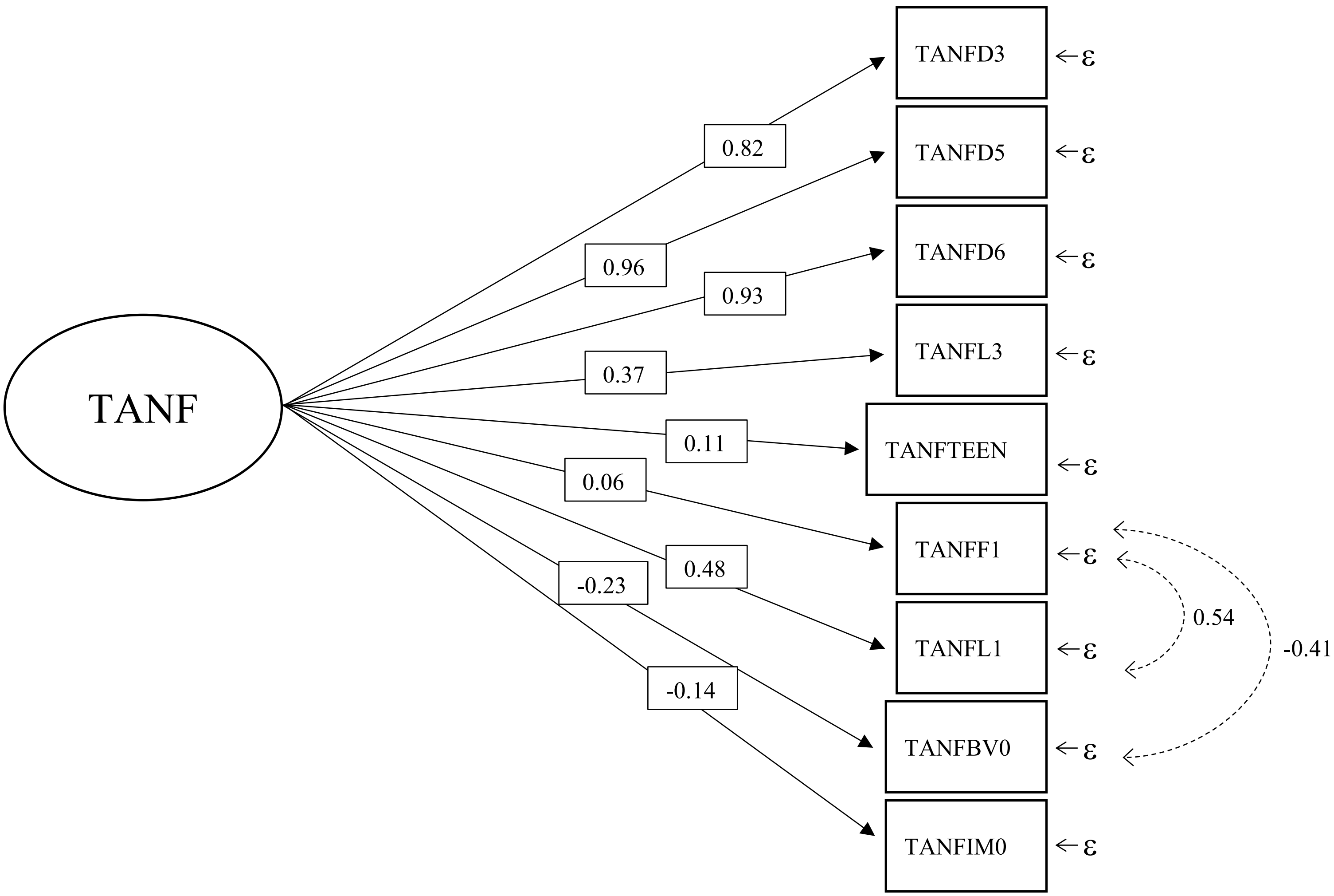
Factor of SNAP Program Generosity



Note. FS = Food Stamps; SNAP = Supplemental Nutrition Assistance Program.

Figure 2.26

Factor of TANF Program Generosity



Note. TANF = Temporary Assistance to Needy Families.

Conclusion

Ultimately, the preferred method for aggregating the social safety net regulations database created in Paper 1 was by using a simple index. Despite testing three different conceptions of how latent generosity might be influencing observed program regulations and administration, I was unable to model accurately this construct. It is possible that a latent generosity does underlie the setting of program rules by states; however, the indicators pulled from the Paper 1 database cannot explain it using the configurations in my hypothesized models.

The existence of well-fitting smaller models (e.g., those regarding indicators of asset tests or coverage for immigrants) does imply that there might be a multitude of underlying latent traits or attitudes that affect administration and regulation of these safety net programs. However, it might imply that they do not do so in the same way for all three programs or for all different types of indicators. More work must be done to determine exactly which indicators move in tandem and so indicate that they are the result of a common latent characteristic of a state-year. It is possible that the latter is likely because, although indicators that address the application processes have a common underlying trait for SNAP and Medicaid, but not for TANF, yet indicators that address income eligibility are commonly motivated for TANF and Medicaid, but not for SNAP. The latter occurs because, absent BBCE, SNAP's income eligibility level (if not its certification) is set by the federal government,

The key difference between constructing a generosity index and a generosity scale was the difference in the directionality of generosity's relationship with the safety net indicators. What the above analyses show is that the hypothesized way in which underlying generosity would have an impact on the policies of these three safety net programs does not exist in any of the ways I predicted that it might; however, the impact of the program indicators on the generosity climate in which program workers and participants exist is undeniable. I cannot say with certainty that generosity or some other latent trait causes the variation in the indicators, but that the variation in the indicators is assuredly causing changes in the way that the programs are experienced. Therefore, the questions surrounding the index are “How much of an impact does each indicator have on that experience?” and “Are the indicators included in the Paper 1 database sufficient to account entirely for that climate?”

Future work on the generosity index should focus on explaining the extent of the impact of these indicators by validating the score, using measures of employee and participant experiences within the social safety net system. If the index is intended to measure the assistance climate that is felt by the people within the system, it is important to ask those individuals what their experiences are. The naïve index indicates that states in the Northeast and on the Pacific coast are the most generous, while the South lags behind: Does this pattern reflect the opinions of the people receiving and administering assistance?

The index can be validated further by combining it with objective outcome measures. The original and continuing goal of the Food Stamp Program was to alleviate hunger and to allow all Americans access to food. Medicaid was aimed at improving the population’s health and TANF was aimed at alleviating poverty among families (along with other goals that came with the switch from AFDC to TANF, e.g., helping parents to become employed and reducing the rate of out-of-wedlock births). Although the index is not intended to evaluate the success of these programs relative to their stated goals, it can in the future be refined by comparing it to certain population-level factors that are known to correlate with generous social assistance and by measuring the relative contribution of each indicator that composes the index.

Although the index as it exists now is a crude measure for the assistance climate, it does offer an effective way to include a number of facets of the social safety net into the analyses of population outcomes. By aggregating all of the policies measured in Paper 1, the index allows researchers a single measure to use in analyzing any number of social or economic indicators. In the third and final paper of this dissertation, I employ the index to examine the role of assistance policy among the social determinants of public health outcomes, in this case the rate of maternal mortality in the United States.

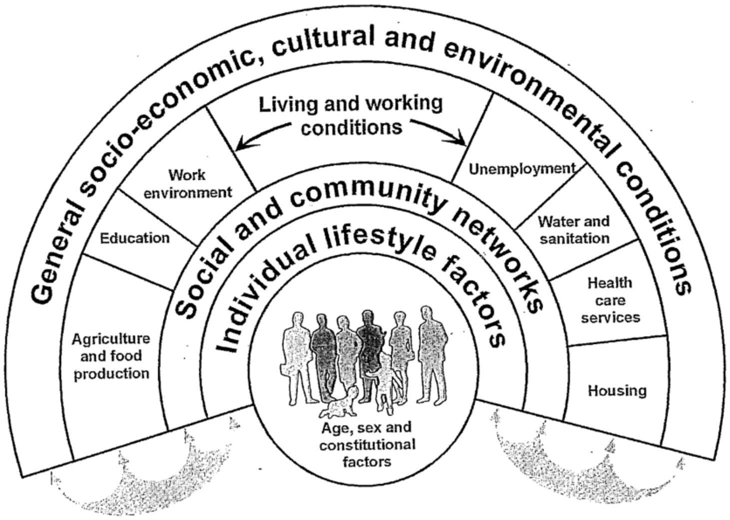
PAPER 3: ASSESSING THE IMPACT OF THE SOCIAL SAFETY NET ON MATERNAL BIRTH OUTCOMES ACROSS THE UNITED STATES

Section 3.1 Social Determinants of Public Health

Health is more than a combination of biology and medicine; one's health status and that of a society are determined by myriad factors both individual and population-wide. In the last 30 years, public health scholars have recognized that the inequities in health status can have deleterious effects on vulnerable populations, exacerbating existing injustices, and that, in ameliorating these inequalities, stakeholders must rely on more than advances in medicine and healthcare provision. In this time, scholars have extended focus to the social determinants of health as well as the biological and medical ones. With this framework, I recognize that health status is determined by a range of factors that are both proximate (individual lifestyle factors, e.g. drinking or eating habits) and distal (societal factors, e.g., living conditions and socioeconomic environment). Dahlgren and Whitehead (1991) conceived of this layered model that moves from the proximate to the distal (see Figure 3.1).

Figure 3.1

Dahlgren and Whitehead Model of Main Determinants of Health



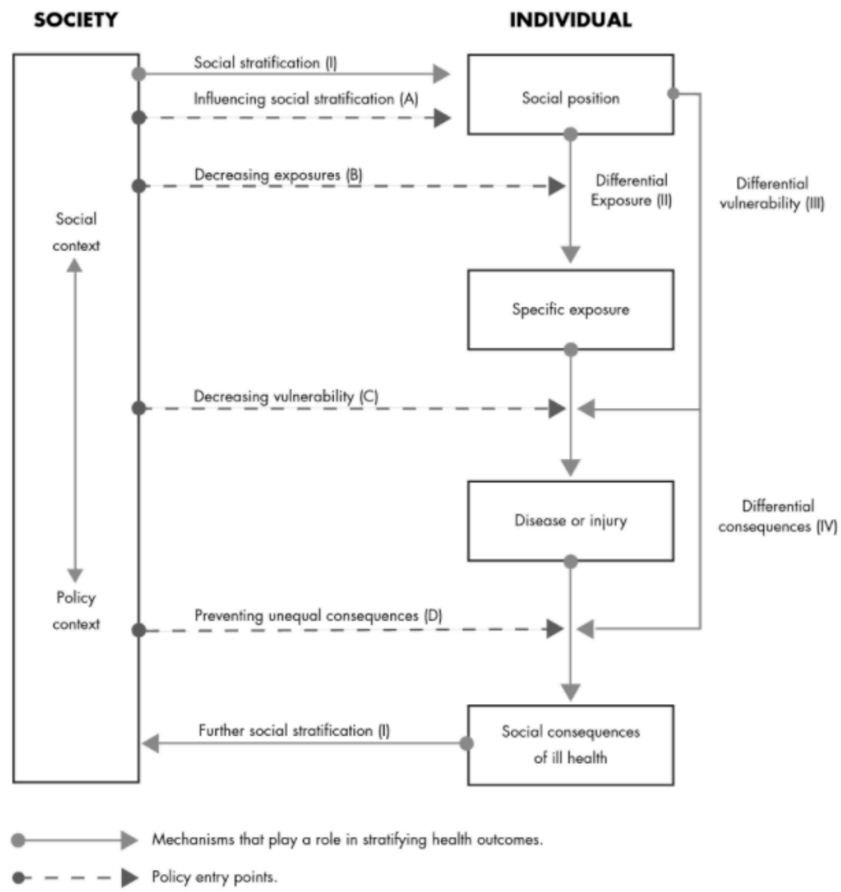
Note. From "Policies and strategies to promote social equity in health. Background document to WHO," by G. Dahlgren, & M. Whitehead, 1991, in *Strategy Paper for Europe* (pp. 4–41). Institute for Future Studies.

Inequalities in health often mirror inequalities in other areas (e.g., income or access to services; Bonner, 2017; Kawachi, Kennedy, Lochner, & Prothrow-Stith, 1997; Lundberg, Yngwe, Stjärne, Elstad, Ferrarini, Kangas, Norström, Palme, & Fritzell, 2008; Income, health, and social welfare policies, 2020). In looking beyond individual and biological determinants of health, policymakers have the ability to generate large improvements in health inequities by targeting other inequities or broader social factors (Blas, Gilson, Kelly, Labonté, Lapitan, Muntaner, Östlin, Popay, Sadana, Sen, Schrecker, & Vaghri, 2008; Marmot, Friel, Bell, Houweling, & Taylor, 2008; World Health Organization, n.d.). Building on the social determinants of health framework, this dissertation attempts to explore the two outer rings of the Dahlgren and Whitehead model: general socioeconomic, cultural and environmental conditions as well as living and working conditions. It is within these two rings or layers that public policy lives, representing the "policy determinants of health" as a subset of broader social determinants.

The points at which policy intersects with the social determinants of health model can be seen in the Diderichsen model (Diderichsen, Evans, & Whitehead, 2001):

Figure 3.2

Diderichsen Model of Social and Health Inequities



Note. From "The social basis of disparities in health," by F. Diderichsen, T. Evans, & M. Whitehead, 2001, in *Challenging inequities in health* (pp. 13-23). Oxford University Press.

According to this model, public policy has potential to influence individual and population health by influencing the degree of social and economic inequality in a society, by decreasing an individual's "exposure" to dangerous risk factors that are correlated with their social position, decreasing an individual's vulnerability to those exposures and preventing unequal health outcomes that arise as a consequence of these. Public health scholars, particularly the World Health Organization's Commission on the Social Determinants of Health, have called on researchers and policymakers to consider the political and social factors in models like these to aim for improvements in population health measures (Blas et al., 2008; Solar & Irwin, 2007).

Research has been slow to connect the effects of "nonhealth" policies on health outcomes (Rudolph, Caplan, Ben-Moshe, & Dillon, 2013). A great deal of research has been focused on state variation in the "social determinants" of health, most notably state-level income inequality; however, few, if any, researchers examine how redistributive policies correlate with health outcomes—the so-called "causes of the causes" (Olson, Diekema, Elliott, & Renier, 2010; Pega, Kawachi, Rasanathan, & Lundberg, 2013). Social safety net programs constitute the major sources of income redistribution in the United States; therefore, they affect proximal and distal determinants of health through direct mechanisms (increased access to income, nutritious food, and medical care); indirect mechanisms (including stress, stigma, economic insecurity); and contextual effects (decreased poverty and inequality and increased and social capital; (Kawachi et al., 1997; Pickett, 2002; Soss, 1999). Where states have been granted discretion in determining eligibility for and monetary support of these safety net benefits, it is possible to examine these state laws to assess welfare generosity. Researchers have begun to examine the direct health effect of participation in individual state programs; however, in their studies, they have not looked to the overall social welfare generosity of a state (combining the effects of multiple laws) on the environment necessary for public health (Wise, Chavkin, & Romero, 1999). Therefore, my contention is that these jurisdictional differences in policies (statutory or procedurally) lead to differences in health outcomes because the assistance that people receive can vary so widely.

In looking at the outermost rings of the social determinants of health (SDH) model, one can see how the "generosity" of social policy influences public health. Where it has long been understood that sociodemographic status is a fundamental underlying determinant of health outcomes, the generosity of a social welfare system is thought to provide social protection and to affect health outcomes independent of household income. Although, household income and other personal factors lie within the two smallest layers or rings of the Dahlgren and Whitehead model, the robustness of a society's social services lies further out. As the United States has delegated the administration of many social safety net programs to the states, these subnational entities are now increasingly responsible for establishing the eligibility, enrollment, and the value of benefits for these safety net programs, as well as for their administration. Thus, the combined effect of these laws, policies, and regulations can perhaps serve as a measure of the generosity of a state's social welfare system. This effect of the wider social welfare environment raises an imperative to study the range of redistributive safety net policies across the states.

In this paper, I use the measure of welfare generosity created in the previous paper as an independent variable in an analysis of a particular public health outcome, maternal morbidity. Maternal health and infant health are some of the most important population health indicators, and they are very much socially determined. Numerous studies have already applied the social determinants of health framework to perinatal health, looking at how political, social, and economic factors affect maternal and infant mortality. The latter, in particular infant mortality, is found to be very sensitive to public health investment and intervention (Bradley, Elkins, Herrin, & Elbel, 2011; Chung & Muntaner, 2006; Conley & Springer, 2001).

Birth outcomes, like other health indicators, depend most immediately on the quality and type of medical care that a mother[3] receives, as well as preexisting risk factors attributable

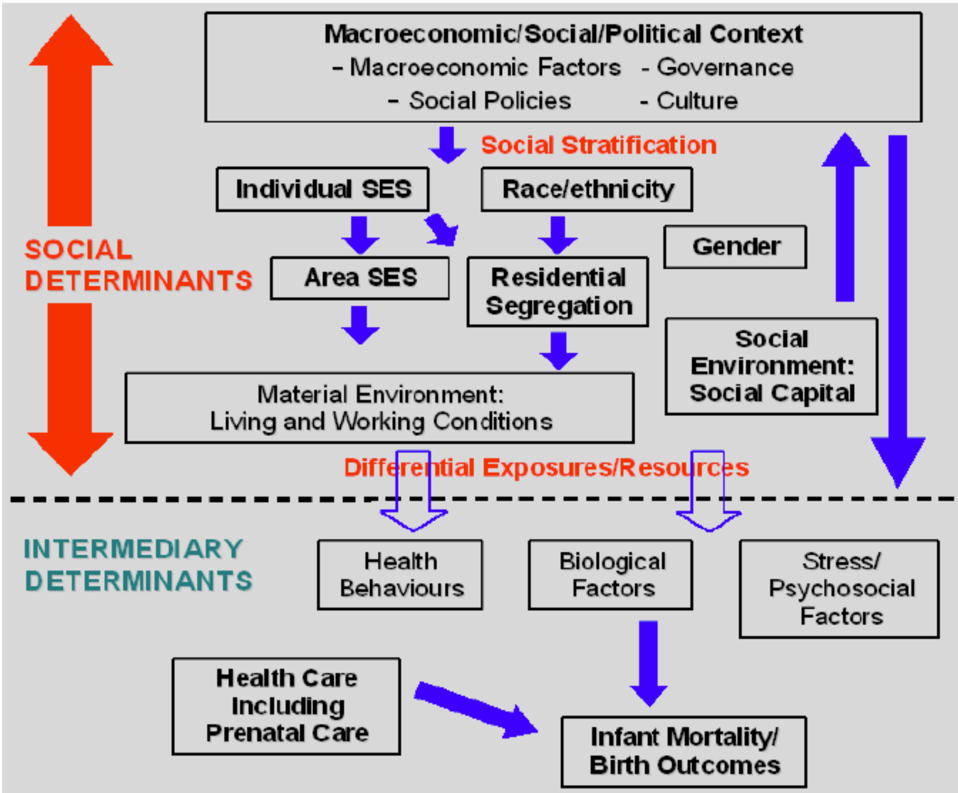
[3] In this paper, I will refer to "women" and "mothers" when discussing pregnancy and perinatal health; however, this is merely in deference to the convention within the literature cited. I would like to acknowledge that not all those who become pregnant or bear children identify as women.

largely to genetics and to the mother's baseline health status. However, even a mother's preexisting health status as well as population, rather than individual, biological risk factors can be thought of as more intermediate determinants of birth outcomes, along with prenatal care, health behaviors and the environment in which gestation happens. These intermediate factors are influenced by the more distal social determinants of health, as illustrated in Figure 3.3. Mothers who are of a lower social or economic position within society, in addition to lacking adequate medical coverage and often being in worse health at the outset, are subject to environmental factors and engage in health behaviors that are associated with worse health at birth for infants (Aizer & Currie, 2014). The intermediary determinants that create the pregnancy environment do very much depend on social and economic status; a mother's social status as well as the differential effect on pregnancy and birth exerted by her social position can be determined or ameliorated through social and health policy.

With this framework, I demonstrate how social policies and governance can affect a society's degree of social stratification, especially of the material and social environments in which a mother becomes pregnant. Within this framework, social policy is a more distal determinant of birth outcomes, although it also plays a role that is proximate through health policy. This role is most notable through public provision of public health coverage (see Figure 3.3), which allows for access to and better quality of the healthcare and prenatal care to which Kim and Saada refer as an intermediary determinant of infant mortality.

Figure 3.3

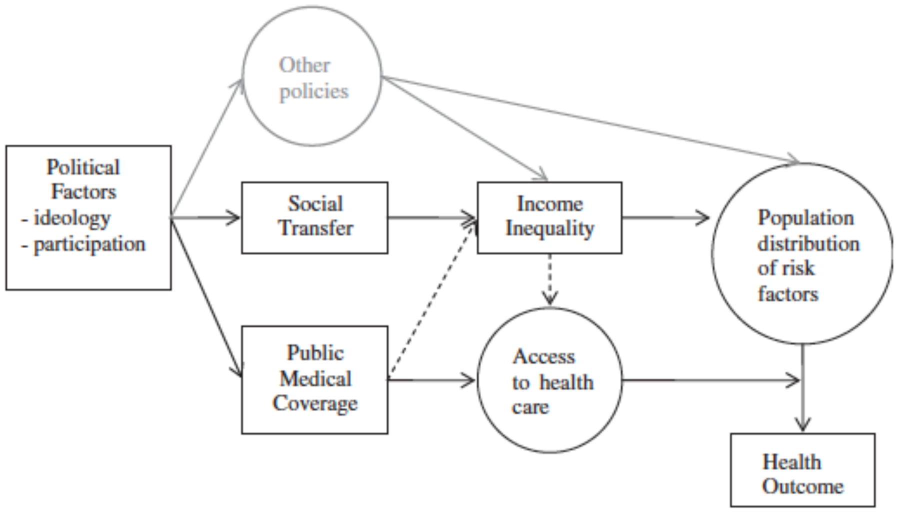
Kim and Saada Framework of Social Determinants of Infant Mortality



Note. From "The social determinants of infant mortality and birth outcomes in western developed nations: A cross-country systematic review," by D. Kim, & A. Saada, 2013, *International Journal of Environmental Research and Public Health, 10*(6), 2296–2335.

Figure 3.4

Chung and Muntaner Model of Political Determinants of Health Outcomes

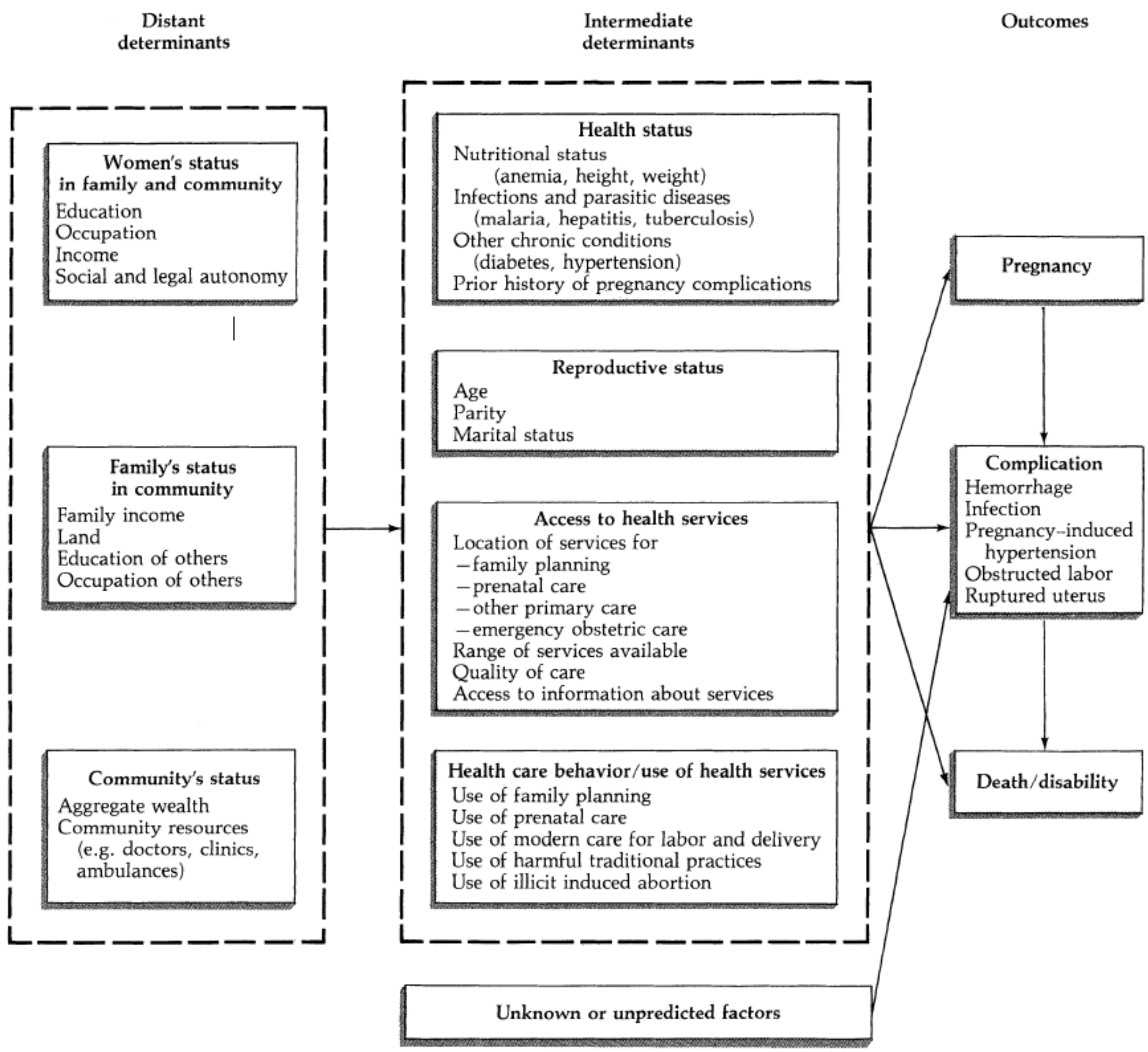


Note. From “Political and welfare state determinants of infant and child health indicators: An analysis of wealthy countries,” by H. Chung, & C. Muntaner, 2006, *Social Science and Medicine, 63*(3), 829–842.

The prevailing conceptual framework examining the determinants of maternal mortality fails to consider the influence of policy on maternal health. Although the distant determinants in McCarthy and Maine’s (1992) model refer to socioeconomic and cultural factors, their more detailed enumeration of those factors makes no mention of prevailing public policies, nor does their enumeration of intermediate determinants refer to social safety net policies that affect a woman’s health status, access to health services or use of health services (see Figure 3.4). Although reference is made to conditions that public policy affects (e.g., the social and legal rights of women in society, or the resources available in a community), the explicit role that safety net policies in particular can play in influencing maternal health is missing. In part, this might be because the framework (as initially conceived) was not meant to apply exclusively to the United States, whose enormous wealth and relatively high mortality ratio make it a unique case in a field where much of the research on societal and economic determinants of mortality arise much more frequently in poorer countries or regions.

Figure 3.5

McCarthy and Maine Framework of Determinants of Maternal Mortality



Note. From "A Framework for analyzing the determinants of maternal mortality," J. McCarthy, & D. Maine, 1992, *Studies in Family Planning, 23*(1), 23.

An alternative framework for examining the social determinants of maternal health (rather than broader population or infant health) within the context of a wealthy society like the United States would be to consider everything beyond access to and quality delivery of healthcare to be more distally influential on a mother's health and that of her infant. The system-wide decisions that surround healthcare policy and financing are so critical at every step along the "continuum of maternity care" that even the social and material environment in which a mother carries out her pregnancy is more distal to the birth outcome (see Figure 3.6). This model is unlike previous models of maternal mortality in which the mother's socioeconomic status is second only to her health status in determining her risk of adverse birth outcomes (Filippi, Chou, Barreix, Say, & the WHO Maternal Morbidity Working Group, 2018).

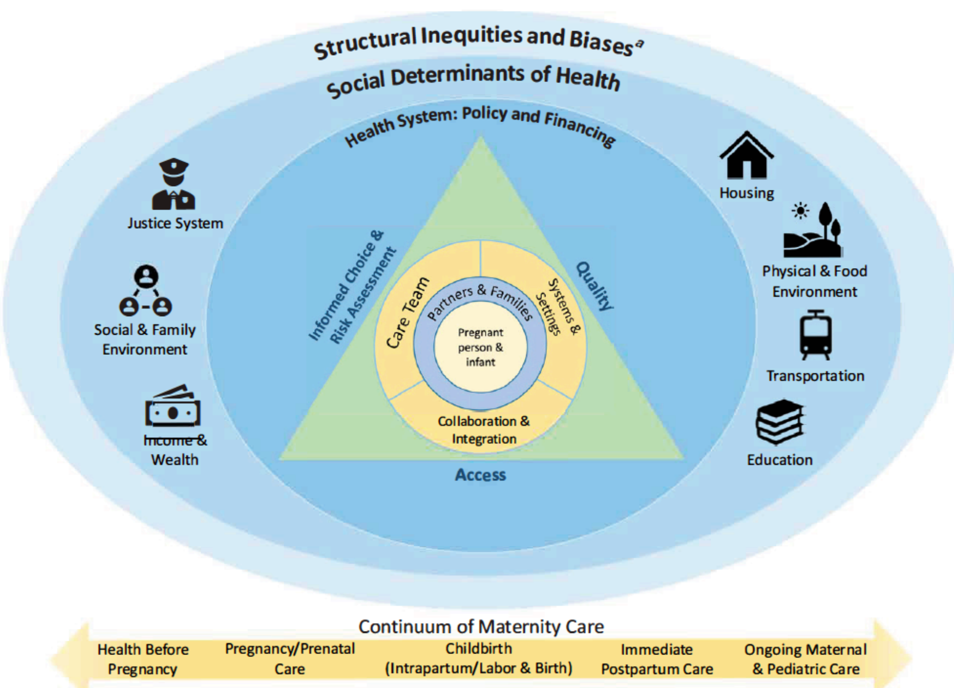
Regardless of the chosen framework, it is clear that the generosity of social safety net programs as measured in Paper 2 can have an impact on maternal health. Although Medicaid obviously affects prenatal and healthcare delivery, it also plays a role (along with SNAP, TANF and other social assistance or income transfer programs) in determining the mother's preexisting health status, the environment in which she is pregnant, and her social and economic status, as well as population-wide inequality and deprivation.

MCH is critical not only because it is sensitive to state interventions as a health outcome, but also because infants who are born healthy to healthy mothers are advantageously positioned for the rest of their lives. Investments by policymakers in MCH can produce double dividends by improving health of mother and child in the near term and of the child throughout its life long term. The Fetal Origins of Adult Disease hypothesis holds that certain risk factors for a number of chronic health conditions in adulthood depend on the development in utero and can be affected by nutrition and stress (Almond & Currie, 2011; Barker, 1995, 1999; Calkins & Devaskar, 2011). Low birthweight (LBW) infants have worse life outcomes, both immediately, with LBW infants at higher risk of mortality within the 1st year, and long term, with worse educational or earnings prospects (Aizer & Currie, 2014; Black, Devereux, & Salvanes, 2007).

The effects of LBW infants continue even into the next generations, as a mother who was born at a LBW is much more likely to have a child who is also of LBW (Currie & Moretti, 2007). The Diderichsen model (Figure 3.2) shows how poor health and its social consequences are part of a feedback loop that leads to further social stratification and that serves as an input to the social determinants of health framework (Diderichsen et al., 2001). In this way, policy interventions that target gestation can have impacts not only on lower or more microlevel health determinants, but also on higher level or more macrolevel factors.

Figure 3.6

Alternative Conceptual Model of Social Determinants of Maternal Health



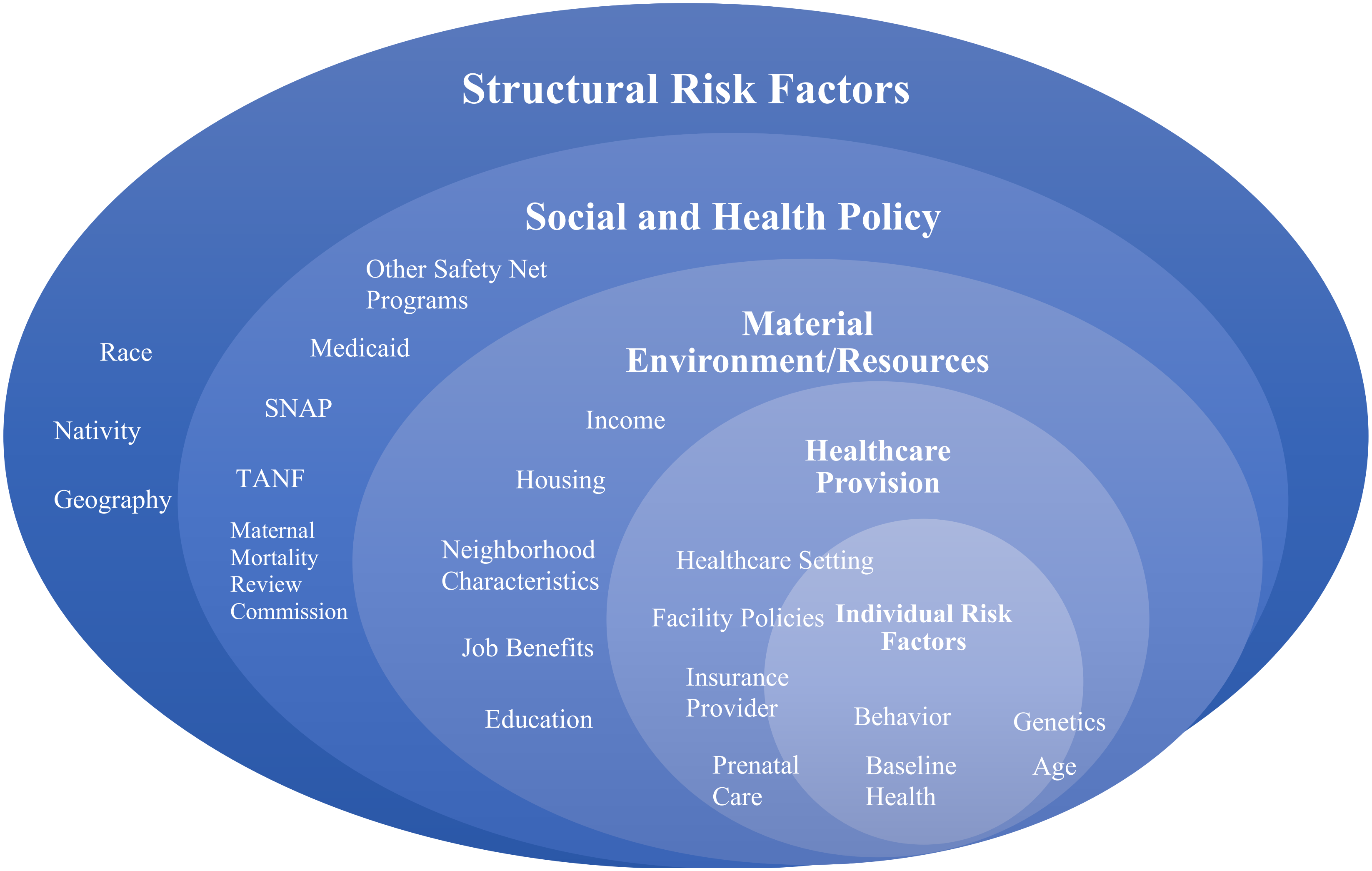
Note. From *Birth settings in America: Outcomes, quality, access, and choice* (S. C. Scrimshaw & E. P. Backes, Eds.), by Committee on Assessing Health Outcomes by Birth Settings, Board on Children, Youth, and Families, Division of Behavioral and Social Sciences and Education, Health and Medicine Division, and National Academies of Sciences, Engineering, and Medicine, 2020. National Academies Press.

Section 3.2 A New Theoretical Framework for Maternal Health

Integrating the aforementioned perinatal health frameworks with the broader social determinants of health frameworks referenced in Paper 1, in this paper, I employ a theoretical framework to guide the analysis. In this framework, I envision concentric circles in which each circle has an impact on the smaller circles fitted within it. The outermost circles can be thought of as the macrolevel factors that influence the intermediary factors and that in turn influence the microlevel factors. Each level can be influenced by not only the level immediately superior to it, but also any or all of the anterior factors.

Figure 3.7

Theoretical Framework



The outcome of interest is maternal mortality. According to the Centers for Disease Control and Prevention (CDC; 2020), pregnancy related deaths in the United States peaked in 2014, with 18 deaths per 100,000 live births. The latest data from 2016 shows a ratio of 16.9 deaths per 100,000 live births. Between 2011 and 2016, the leading causes of pregnancy-related deaths were hemorrhage, infection, cardiomyopathy, and other cardiovascular conditions (CDC, Division of Reproductive Health, 2020a). Although hemorrhage was long the leading cause of maternal death, its proportion has been falling and in recent years, the fraction of deaths caused by diseases of the heart and blood vessels has increased such that they are now the leading cause of maternal death (Callaghan, 2012). Cardiovascular-related maternal deaths are even more strongly affected by preexisting conditions and by the factors listed in my framework. The shifting burden of maternal death towards these more socially determined conditions means that understanding these social determinants is more important than ever.

Pregnancy-related mortality in the United States has been increasing in the 21st century following a century of decline. Not all of the increase is rooted in the social determinants framework. Some of the increase can be attributed to exogenous factors, including increased detection of maternal deaths because of changes in American death certificates and advancing maternal age as women choose to start families later in life than their counterparts in previous generations (pregnancies in women over Age 35 and especially over Age 40 are inherently riskier). However, the fact remains that the risk of maternal death is higher now than it was 20 years ago (Berg, 2012; Berg, Callaghan, Syverson, & Henderson, 2010; Callaghan, 2012; Creanga, Berg, Ko, Farr, Tong, Bruce, & Callaghan, 2014; Creanga, Berg, Syverson, Seed, Bruce, & Callaghan, 2015; MacDorman, Declercq, Cabral, & Morton, 2016).

The leading causes of maternal death are hemorrhage, infection, amniotic fluid embolism, thrombotic pulmonary embolism, hypertensive disorders, complications from anesthesia, cerebrovascular accident, cardiomyopathy, other cardiovascular conditions and other noncardiovascular health conditions (CDC, Division of Reproductive Health, 2020a). Although some of these deaths are unavoidable and tragic consequences of childbirth, which always has an attached risk, it is hypothesized that anywhere from 40% to 66% of maternal deaths in the U.S. are preventable (Berg, 2012; Berg, Harper, Atkinson, Bell, Brown, Hage, Mitra, Moise, & Callaghan, 2005; Davis, Smoots, & Goodman, 2019; Petersen, Davis, Goodman, Cox, Mayes, Johnston, Syverson, Seed, Shapiro-Mendoza, Callaghan, & Barfield, 2019). Some strategies to reduce these deaths are related to implementing obstetric best practices and relying on hospitals and other medical providers to act; however, a number of these avoidable deaths are rooted in social disparities that expose mothers of different socioeconomic statuses or racial and ethnic groups to differential risk of experiencing maternal morbidity or mortality.

Perhaps the greatest indication that maternal mortality is largely socially determined is the enormous racial disparities that exist. The maternal mortality ratio is 3–4 times higher for non-Hispanic Black women than it is for non-Hispanic White women, and it is also up to 2 times higher for indigenous (Native American and Alaska Native) women than for non-Hispanic White women (Bryant, Worjoloh, Caughey, & Washington, 2010; Creanga et al., 2014, 2015; Kozhimannil, Interrante, Tofte, & Admon, 2020; Louis, Interrante, Tofte, & Admon, 2015; Metcalfe et al., 2018). In fact, the leading causes of maternal mortality differ by race, with White women more likely to die of conditions such as hemorrhage and infection, while Black women are more likely to die of cardiomyopathy and preeclampsia or eclampsia, where the latter conditions have strong associations with a mother's preexisting health status in a way that the former do not (Davis et al., 2019).

Race certainly has a direct effect on a mother's health both before and during pregnancy and childbirth: exposure to the structural racism underlying American society puts stress on Black women, increasing allostatic load and causing a "weathering" effect that gets worse with age. Furthermore, Black women's past experiences with the medical system, both personally and as a group, are often the cause of mistrust and avoidance of seeking care (Geronimus, 1996; Louis et al., 2015; Rosenthal & Lobel, 2011; Wallace, Harville, Theall, Webber, Chen, & Berenson, 2013). Race also has an indirect effect in that it affects numerous other social determinants, from residential segregation driving neighborhood characteristics to the generosity of a state's welfare program (states with higher Black populations tend to operate less generous TANF programs; Hahn, Aron, Lou, Pratt, & Okoli, 2017; Wallace et al., 2013).

Other factors leading to differential rates of maternal mortality include geography, income, education, and insurance status, many of which affect one another in turn. Low-income women and those with a high school education or less are likelier to lack access to adequate nutrition, housing, and medical care, not least because they are less likely to have insurance. These factors affect not only a woman's health during pregnancy, but also have a huge impact on her baseline level of health. Poor preconception health leads to a higher risk of maternal death, especially conditions such as hypertension, diabetes, and obesity which are in themselves associated with low socioeconomic status. Lack of education and insurance can also lead to riskier health behaviors (e.g., smoking or failure to seek prenatal care), which can also lead to adverse birth outcomes (Creanga et al., 2014; Nelson, Moniz, & Davis, 2018).

Where a woman lives will often end up having huge impacts on her risk of maternal death. Rural residents have much less access to hospitals and specialized medical care, especially in recent years as more and more hospitals in rural areas shut down or cut back their services. Many rural areas lack appropriate obstetric care, and as a result, childbirth is a riskier proposition in those areas, especially if a delivery requires extreme intervention (Kozhimannil, Hung, Henning-Smith, Casey, &, 2018, Kozhimannil et al., 2020). In addition to proximity to care, where a mother resides affects her risk because of a number of policies that are made at the state level.

Although calls for a national maternal mortality review committee (MMRC) have been increasing, a number of states have established their own bodies tasked with undertaking a review of maternal deaths in that state, with the goal of understanding what can be done differently to reduce the number of those deaths (Berg, 2012; Clark & Belfort, 2017). Currently, 25 states are working with the CDC to run their own MMRCs through their ERASE MM initiative in addition to maternal mortality reviews that take place outside of this framework. Within larger states, localities even conduct their own processes for reviewing maternal deaths. Evidence from countries with existing bodies in place to review maternal deaths demonstrates the benefit of these committees (CDC, Division of Reproductive Health, 2020b; Lewis, 2012).

States play an enormous role in the types of support offered to mothers. From traditional safety net programs such as SNAP, Medicaid, and TANF, to more specialized programs like WIC, decisions by policymakers at the state-level might mean that women in states offering greater assistance could have a lower risk of maternal death. However, although theoretically reasonable and in line with the maternal mortality frameworks, the evidence for this does not yet exist. Most of the research on determinants of maternal mortality focuses on individual or facility level determinants. Evidence from MMRCs, which has been of enormous benefit, has focused on the intersection of mothers and the healthcare system. MMRCs often involve a number of obstetricians reviewing cases of maternal death to see how it could have been avoided. There is nothing in a case review by a physician that can speak to the role of social policy.

Much of the research involving maternal mortality is carried out at the individual level, looking at individual risk factors for experiencing an adverse maternal birth outcome. Some of these factors are largely exogenous to social determinants (e.g., parity), while some are clear manifestations of social determinants (e.g., race or ethnicity). However, state-level analyses of maternal mortality are lacking. Only in the last few years has variation in states' maternal mortality ratios are being probed using state-level data (Eliason, 2020; Nelson et al., 2018; Vilda, Wallace, Dyer, Harville, & Theall, 2019). These few studies have shown an association between state-level factors (e.g., Medicaid expansion and state-level income inequality with maternal mortality), but none have yet tested the impact of more than one safety net program or their relative generosity.

Section 3.3 Analysis

The treatment variable of interest for this analysis is the generosity of a state's social safety net, as measured using the naïve index constructed in Paper 2. The outcome of interest is the maternal mortality ratio. The data on maternal deaths come from the National Center for Health Statistics' (NCHS; 2017a) Vital Statistics System. NCHS's detailed mortality files contain an entry of every death recorded in the United States in a given year, including basic demographic information about the decedent, information about their cause of death (both the underlying cause of death as well as conditions occurring in sequence that led to death), geographic information (the limited geography files include only the state where it occurred) and, in some although not all cases, information on whether the decedent was pregnant at the time or death or within the previous year.

Information on cause of death as well as comorbid conditions were recorded by the Division of Vital Statistics, using the International Statistical Classification of Diseases and Related Health Problems 10th Revision (ICD 10), a three-digit code consisting of a letter, which indicates the broader category of the disease or condition, followed by a two-digit number indicating the specific condition or disease (the three-digit categories can be further subdivided into four-digit subcategories in which an additional number is added to the original code following a period). Conditions related to "pregnancy, childbirth and the puerperium" are coded from O00 to O99, and code A34 for "obstetrical tetanus" can also be considered a maternal death (World Health Organization, 2019). Although many studies of maternal mortality do not consider deaths coded as O96 (deaths from obstetric causes occurring more than 42 days, but less than 1 year after childbirth) and O97 (deaths from sequelae of obstetric causes) to be maternal deaths, I have chosen to include them because I am not only interested in deaths occurring immediately or directly following childbirth, but deaths that are in any way related to having given birth. Data regarding the number of births in a state in each year were gathered from the limited geography natality files from NCHS (2017b).

I generated two different estimates of the maternal mortality ratio. In the first estimate, I counted only deaths that were directly attributed to an obstetric cause. In the expanded MMR, I counted not only deaths where the underlying cause of death was coded as A34 or from O00–O99, but also deaths in which one of those codes was indicated on the death certificate even if it was not the underlying cause of death. Although it is possible that this process led to my capturing some deaths that were unrelated to the pregnancy, it is unlikely that a significant number of death certificates in which the death was unrelated to pregnancy or childbirth included codes reserved for conditions arising therein.

For both births and deaths, I generated two types of measures: those occurring in the state and measures applying to residents of that state. Death certificate data includes not only the state of occurrence, but also the state in which the decedent lived; the same is true for birth certificate data, which contains the mother's state of residence as well as the state where the birth took place. Safety net programs are only available to individuals in the state where they reside; therefore, the "treatment" of interest in this analysis—the generosity of a particular state's safety net—is more accurately judged to have affected residents of a particular state, regardless of where they gave birth or died, rather than those whose labor and delivery or death occurred in that state.

Selection of other variables of interest drew primarily from Nelson et al.'s (2018) analysis of population-level factors that are associated with American maternal mortality. The factors that were individually associated with state-level MMRs addressed the proportion of births to women carrying a number of different risk factors (e.g., certain health conditions, advanced age, Black race, or delivery via cesarean) as well as state demographic characteristics (e.g., the uninsurance rate among women of childbearing age or the median household income). Ultimately, the authors were able to explain 91% of the variation in state-level maternal mortality using six indicators:

- whether a state had adopted the 2003 revision to the death certificate by 2011;
- the proportion of women of childbearing age with a BMI ≥ 30;
- the proportion of births to women with diabetes;
- the proportion of women of childbearing age not having completed high school/GED;

- the proportion of births to women who attended fewer than 10 prenatal visits;
- the proportion of births to Black women.

Data on the proportion of births to women with a particular characteristic (whether health status or race) were also generated using the limited geography natality files (NCHS, 2017b). Estimates on the demographics and population of each state were generated using data from the Surveillance, Epidemiology, and End Results Program on the American population from 1966–2018 (U.S. Department of Health and Human Services, National Institutes of Health, National Cancer Institute, Division of Cancer Control and Population, Surveillance Research Program, 2019). Additional state-level data on social safety net programs as well as poverty and employment rates in each state were gathered from national welfare data at the University of Kentucky Center for Poverty Research (2020). Natality data are only accessible through 2012[4]; therefore, the timeline of the observations is for the years 2005–2012. Data on educational attainment for women as well as obesity rates were attained from the Behavioral Risk Factor Surveillance System at the CDC's (2015) National Center for Chronic Disease Prevention and Health Promotion, Division of Population Health.

The data regarding whether a state had implemented the 2003 revised death certificate is not easily available. Although Nelson et al. (2018) received this information from contact with individuals at NCHS and the CDC, restrictions put into place because of COVID-19 meant that this avenue was not easily available to me. The best proxy I was able to render for whether a state had adopted the 2003 revision of the death certificate was whether an individual's death record in the mortality files contained an observation for the level of education according to the

[4] Although natality data exists in every year, technical difficulties accessing the data through NCHS, especially following the outbreak of COVID-19 (Coronavirus Disease 2019), meant that I was unable to receive uncorrupted files for years after 2012 or before 2005.

2003 revision, instead of an observation for education according to the 1989 revision; for every recorded death contained an observation for one of these two indicators.

Between 2005 and 2016, in nine state-years some but not all of the death certificates were issued in the 2003 revised version; these years indicate the time during which the state was changing from the 1989 revision of the death certificate to the 2003 revision. In these transition years, 5% to 78% of the death certificates issued were by a state in which the new revision was used. Nelson et al. (2018) used a single indicator for whether a state had adopted the 2003 revision by 2011 (37 states, if they are including Minnesota, adopted the certificate in 2011 and issued 78% of its death certificates using the revised version). In any case, Nelson et al.'s intention was to explain the large jump in maternal mortality over a specific time period, while I am attempting to look at variation across time and space; therefore, I used an indicator for each state year that indicated the proportion of the death certificates that were issued in a state in a year that in which the state used the 2003 version.

Table 3.1

Adoption of 2003 Revision of Standard Death Certificate

Adopted 2003 Revised Death Certificate prior to 2005	California, Connecticut, Florida, Idaho, Kansas, Michigan, Montana, Nebraska, New Hampshire, New Jersey, New York, Oklahoma, South Carolina, Utah, Washington, Wyoming
2005	District of Columbia (77%)
2006	New Mexico, Oregon, Rhode Island, Texas
2007	Delaware, Ohio
2008	Arkansas, Georgia, Illinois, Indiana, Nevada, North Dakota, Vermont (50%)
2010	Arizona, Kentucky (56%), Maine (5%), Missouri,
2011	Iowa, Minnesota (78%)
2012	Louisiana (49%), Mississippi, Pennsylvania, Tennessee,
Never adopted 2003 Revised Death Certificate	Alabama, Alaska, Colorado, Hawaii, Maryland, Massachusetts, North Carolina, Virginia, West Virginia, Wisconsin

In this analysis, I employed multilevel maximum likelihood regression with a random intercept to account for the clustering of yearly data within states, continuing the analysis that Nelson et al. (2018) began. However, I did not limit deaths to those within 42 days of delivery or exclude deaths from sequelae of obstetric causes; therefore, the actual maternal mortality ratio that I employ is slightly different from theirs. Using the factors that Nelson et al. found to be important determinants of maternal deaths as well as my generosity estimates from the naïve index created in Paper 2, I was able to construct models for both the extended MMR (which was calculated from death certificates that mentioned an obstetric cause whether it was the underlying cause of death) as well as for the limited MMR (which confined deaths to those that listed an underlying obstetric cause of death). These two different maternal mortality ratios finally had distinctly different determinants.

In both cases, the most important determinant of maternal mortality by far was the percentage of death certificates issued using the 2003 revision. Additional factors that were significant in Nelson et al.'s (2018) earlier model (either individually or jointly) were not significant in my models, with the exception of the proportion of the female population with a BMI ≥ 30 for the extended MMR, and the proportion of births to Black women for the restricted MMR (see Tables 3.5–3.6). Although I initially included a year fixed effect, and found that the latter years of the panel in particular had significantly higher mortality, the effect of those years vanished with the inclusion of the birth certificate revision variable, leading me to believe that much of that increased mortality was in fact increased detection of pregnancy-related deaths.

Race Stratified Analysis

One cannot discuss maternal mortality in the United States without acknowledging the enormous racial disparities, and evidence that the causes of Black and White maternal mortality are different means that the determinants of the Black maternal mortality ratio are perhaps different from the determinants of the White maternal mortality ratio. Prior analyses have almost all been conducted at the individual level; therefore, a mother's race is easily included as an individual risk factor for morbidity or mortality. However, state-level analyses have rarely looked at the racial differences. Nelson et al. (2018) looked at the proportion of births to Black women; however, that analysis did not reach the fundamental ways in which White and Black maternal mortality differ.

Vilda et al. (2019) found that a determinant could be statistically significant for Black maternal mortality, while remaining insignificant for White mortality. I stratified the models fitted by race, using non-Hispanic White MMRs and non-Hispanic Black MMRs in separate analyses. This necessarily required me to drop the proportion of births to Black women as a control in my limited MMR model. Black MMRs have such enormous variance; therefore, I ran the models both with the extreme outliers and without them. I also considered whether all of the state-years with zero recorded Black mortality were "true zeros" or whether the zeros occurred simply because the state had a very small Black population. I coded the Black MMRs as missing in states in which less than 5% of the female population was Black (19 states in every year, as well as Minnesota in 2 years). This also addressed outliers so that the distribution of MMRs was no longer highly skewed.

Some states have such a smaller number of births to Black women in a given year, for even one Black maternal death can represent a huge proportion of those births and lead to an extremely high MMR in that state-year. Therefore, the maximum value for Black maternal mortality was more than 750 deaths per 100,000 live births (see Table 3.3). Nevertheless, although the Black MMR was certainly multiples higher than the White MMR, it was not seven times higher, or the extreme outlying values that occurred in South Dakota, New Hampshire and Idaho. All states in which the Black MMRs were greater than 125 deaths per 100,000 live births occurred have female populations that are less than 10% Black.

Section 3.4 Results

Included below are the results of the multilevel, maximum likelihood estimation regression that was carried out on the births and deaths that occurred within a state. It is worth noting that the revised death certificate indicator included in these models is much more applicable to analysis carried out on the maternal mortality ratio of maternal deaths to live births that occurred in that state, rather than for residents of a state, for the death certificate is issued by the state in which a person dies rather than the state in which they lived. However, so much of the variation in mortality ratios is attributable to the death certificate revision (see Tables 3.11–12); therefore, it is illogical to carry out analysis that does not include that information. For this reason, although I carried out the analysis using state residents rather than occurrences, I kept in the variable that indicated the death certificate revision because, most births and deaths occur in the state in which one resides. The results of these analyses are included in Appendix 3, while the discussion in this paper is contained in the analysis of births and deaths occurring in a state.

Included in appendix 4 are the results of the fixed-effects versions of each model, both with and without year fixed effects as well as state fixed effects. These results differ from those presented below in that they show no real effects of safety net generosity on maternal mortality.

Analysis of States using 2003 Revised Death Certificates Throughout

Because so much of the variation in MMR is attributable to the 2003 revision of the death certificate, I chose to carry out my analysis on the subset of states that used only the revised death certificate in every year included in the data (see table 3.1). These results are included after the results of the full sample, and they do not include a measure of revised death certificates, since this number would be 1 for all state-years.

Table 3.2

Summary Statistics of State Characteristics

	Mean	SD	Min	Max
Generosity score	51.52	8.16	35.54	74.06
Proportion of women with BMI ≥ 30	0.26	0.04	0.17	0.37
Proportion of women with less than a HS degree	0.10	0.04	0.04	0.20
Median household income in thousands (2018 dollars)	58.80	9.01	40.15	84.97

Note. *N* = 408. BMI = Body mass index; HS = High school; SD = standard deviation.

Table 3.3

Summary Statistics of the Proportion of Births to Mothers with Risk-Factors

	Occurring in a state				Among residents of a state			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Chronic hypertension	0.0137	0.0054	0.0042	0.0340	0.0137	0.0053	0.0042	0.0351
Over 40 years of age	0.0253	0.0095	0.0118	0.0589	0.0252	0.0090	0.0120	0.0555
Diabetes	0.0485	0.0129	0.0182	0.0930	0.0485	0.0127	0.0189	0.0933
Pregnancy-related hypertension	0.0448	0.0112	0.0173	0.0829	0.0448	0.0109	0.0195	0.0799
C-section	0.3069	0.0413	0.2068	0.4033	0.3071	0.0406	0.2082	0.4023
Fewer than 10 prenatal visits	0.2517	0.0710	0.0570	0.4352	0.2529	0.0709	0.0592	0.4339
Black, non-Hispanic	0.1308	0.1184	0.0036	0.4877	0.1326	0.1231	0.0036	0.5776

Note. *N* = 408. SD = standard deviation.

Table 3.4

Maternal Mortality Ratios by Race

	Occurring within a state			Among residents of a state		
	Mean	SD	Max	Mean	SD	Max
Total MMR	25.87	17.45	96.41	26.15	17.57	97.36
Total MMR, limited to UCOD	15.91	10.61	57.94	16.19	11.13	70.40
White MMR	22.64	17.42	99.13	22.72	17.39	99.24
White MMR, limited to UCOD	12.54	10.40	59.69	12.57	11.07	88.61
Black MMR	41.01	62.20	760.46	40.79	62.57	772.20
Black MMR, limited to UCOD	30.76	49.60	552.49	30.70	49.95	549.45
Hispanic MMR	18.49	39.82	477.33	17.14	30.23	269.54
Hispanic MMR, limited to UCOD	11.15	26.26	303.03	10.99	23.95	249.38

Note. N = 408. MMR = maternal mortality ratio; SD = standard deviation; UCOD = underlying cause of death. The minimum maternal mortality ratio for all categories is zero, as there are a number of states with no maternal deaths in certain years.

Table 3.5

Results for Extended Maternal Mortality

	(1)	(2)	(3)	(4)	(5)
	MMR	MMR	MMR	MMR	MMR
Generosity	-0.0932				
	(0.112)				
Revised	18.83***	18.49***	18.75***	18.55***	18.65***
	(1.864)	(1.866)	(1.781)	(1.829)	(1.841)
High BMI	1.016***	0.983***	1.009***	0.941***	0.956**
	(0.271)	(0.287)	(0.26)	(0.271)	(0.296)
SNAP		-0.00923			0.021
		(0.0535)			(0.0575)
TANF			-0.251*		-0.258*
			(0.125)		(0.13)
Medicaid				-0.0481	-0.0258
				(0.11)	(0.115)
_Cons	-6.605	-9.798	-1.303	-6.613	0.581
	(7.913)	(6.935)	(8.026)	(10.1)	(10.79)
X^2	135.16***	133.79***	140.74***	134.26***	141.10***
R^2	0.3074	0.3005	0.3254	0.3038	0.3269

Note. $N = 408$. BMI = body mass index; MMR = maternal mortality ratio. Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.6

Results for Limited Maternal Mortality

	(1)	(2)	(3)	(4)	(5)
	MMR	MMR	MMR	MMR	MMR
Generosity	-0.168*				
	(0.0661)				
Revised	10.18***	10.04***	9.640***	9.707***	10.13***
	(1.12)	(1.135)	(1.098)	(1.114)	(1.12)
Black population	27.08***	27.77***	24.97***	25.71***	26.54***
	(5.333)	(5.541)	(5.414)	(5.467)	(5.415)
SNAP		-0.0635*			-0.0475
		(0.0323)			(0.0335)
TANF			-0.135		-0.103
			(0.0709)		(0.0721)
Medicaid				-0.0783	-0.0436
				(0.0575)	(0.058)
_Cons	15.11***	10.26***	12.38***	11.29***	15.89***
	(3.396)	(2.026)	(3.045)	(3.34)	(3.98)
X^2	97.50***	92.23***	92.96***	89.79***	98.63***
R^2	0.2621	0.2529	0.2548	0.2493	0.2640

Note. $N = 408$. MMR = maternal mortality ratio. Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.7

Results for Extended White Maternal Mortality

	(1)	(2)	(3)	(4)	(5)
	MMR	MMR	MMR	MMR	MMR
Generosity	-0.0582				
	(0.113)				
Revised	17.82***	17.50***	17.91***	17.62***	17.69***
	(1.895)	(1.896)	(1.805)	(1.862)	(1.862)
High BMI	0.883**	0.844**	0.883***	0.845**	0.818**
	(0.27)	(0.286)	(0.259)	(0.274)	(0.296)
SNAP		0.00648			0.0333
		(0.0547)			(0.0586)
TANF			-0.237		-0.253*
			(0.124)		(0.128)
Medicaid				-0.0191	-0.0129
				(0.109)	(0.114)
_Cons	-7.586	-9.784	-1.306	-8.423	-0.129
	(8.096)	(6.978)	(8.067)	(10.25)	(10.84)
X^2	113.89***	113.08***	120.18***	113.30***	120.76***
R^2	0.2808	0.2760	0.3013	0.2778	0.3026

Note. $N = 408$. BMI = body mass index; MMR = maternal mortality ratio; SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.8

Results for Limited White Maternal Mortality

	(1)	(2)	(3)	(4)	(5)
	MMR	MMR	MMR	MMR	MMR
Generosity	-0.206**				
	(0.0676)				
Revised	8.836***	8.623***	8.286***	8.262***	8.754***
	(1.136)	(1.161)	(1.105)	(1.143)	(1.121)
SNAP		-0.0759*			-0.056
		(0.033)			(0.0335)
TANF			-0.196**		-0.165*
			(0.0705)		(0.0716)
Medicaid				-0.0809	-0.0357
				(0.059)	(0.0578)
_Cons	18.06***	12.07***	15.44***	12.25***	19.30***
	(3.45)	(2.039)	(2.866)	(3.314)	(3.89)
X^2	62.25***	55.62***	61.10***	52.30***	66.26***
R^2	0.1791	0.1624	.1781	.1579	.1877

Note. N = 408. MMR = maternal mortality ratio; SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.9

Results for Extended Black Maternal Mortality

	(1)	(2)	(3)	(4)	(5)
	MMR	MMR	MMR	MMR	MMR
Generosity	0.214				
	(0.246)				
Revised	24.22***	24.80***	24.82***	24.49***	24.20***
	(4.026)	(3.991)	(3.903)	(3.946)	(4.024)
High BMI	1.191*	1.123*	1.169*	1.439*	1.350*
	(0.541)	(0.567)	(0.546)	(0.609)	(0.664)
SNAP		0.0561			0.0176
		(0.123)			(0.131)
TANF			0.194		0.135
			(0.269)		(0.28)
Medicaid				0.187	0.147
				(0.215)	(0.232)
_Cons	-9.712	-0.475	-5.705	-15.93	-17.43
	(19.06)	(15.16)	(17.4)	(24.24)	(24.8)
X^2	50.82***	49.86***	50.22***	50.77***	51.19***
R^2	0.2171	0.2124	0.2132	0.2166	0.2183

Note. $N = 254$. MMR = maternal mortality ratio; SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.10

Results for Limited Black Maternal Mortality

	(1)	(2)	(3)	(4)	(5)
	MMR	MMR	MMR	MMR	MMR
Generosity	0.208				
	(0.196)				
Revised	16.05***	16.57***	16.65***	16.50***	16.06***
	(3.178)	(3.158)	(3.106)	(3.138)	(3.181)
SNAP		0.0587			0.041
		(0.0981)			(0.1)
TANF			0.161		0.118
			(0.203)		(0.209)
Medicaid				0.116	0.0904
				(0.143)	(0.145)
_Cons	15.3	22.27***	19.67*	19.35*	14
	(10.05)	(6.19)	(7.959)	(8.148)	(10.66)
X^2	32.12***	30.89***	31.21***	31.17***	32.23***
R^2	0.1425	0.1373	0.1383	0.1378	0.1427

Note. N = 254. MMR = maternal mortality ratio; SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families. Standard errors in parentheses.

* p 0 .05, ** $p < 0.01$, *** $p < 0.001$

Table 3.11

Results for Models Without Generosity Measures

	(1)	(2)	(3)	(4)	(5)	(6)
	MMR1	MMR2	White MMR1	White MMR2	Black MMR1	Black MMR2
Revised	18.41***	9.483***	17.56***	8.022***	25.27***	17.00***
	(1.801)	(1.111)	(1.833)	(1.142)	(3.863)	(3.094)
High BMI	0.965***		0.856**		1.193*	
	(0.266)		(0.267)		(0.547)	
Black population		25.83***				
		(5.562)				
_Cons	-9.822	7.048***	-9.743	7.897***	0.844	25.66***
	(6.936)	(1.217)	(6.969)	(0.942)	(14.94)	(2.471)
X^2	133.73***	86.23***	113.08***	49.34***	49.45***	30.21***
R^2	0.3001	0.2425	0.2762	0.1498	0.2100	0.1338

Note. $N = 408$. BMI = body mass index; MMR = maternal mortality ratio. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.12

Results for Models Including Only Death Certificate Revision

	(1)	(2)	(3)	(4)
	MMR1	MMR2	White MMR1	Black MMR1
Revised	19.62***	8.966***	18.44***	25.88***
	(10.77)	(7.54)	(9.96)	(6.56)
_Cons	14.51***	10.73***	11.97***	32.61***
	(8.26)	(10.31)	(7.04)	(9.65)
X^2	115.90***	56.87***	99.11***	43.02***
R^2	0.2492	0.1602	0.2420	0.1807

Note. $N = 408$. MMR = maternal mortality ratio. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.13

Results for Extended Maternal Mortality, Revised States Only

	(1)	(2)	(3)	(4)	(5)
	MMR	MMR	MMR	MMR	MMR
Generosity	-0.251				
	(0.181)				
High BMI	1.697**	1.565*	1.585*	1.345*	1.668*
	(0.580)	(0.651)	(0.528)	(0.576)	(0.653)
SNAP		-0.0345			-0.0115
		(0.0915)			(0.0953)
TANF			-0.504**		-0.532*
			(0.185)		(0.215)
Medicaid				-0.191	-0.0625
				(0.198)	(0.226)
_Cons	3.628	-3.996	12.57	10.42	8.652
	(14.87)	(14.66)	(14.54)	(20.19)	(20.38)
X^2	8.89*	6.49*	15.29***	7.60*	15.36**
R^2	0.1396	0.0986	0.1942	0.1217	0.1944

Note. $N = 128$. BMI = body mass index; MMR = maternal mortality ratio. Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.14

Results for Limited Maternal Mortality, Revised States Only

	(1)	(2)	(3)	(4)	(5)
	MMR	MMR	MMR	MMR	MMR
Generosity	-0.205*				
	(0.966)				
Black population	21.78	22.89	15.60	16.49	20.87
	(11.38)	(12.52)	(11.76)	(11.80)	(11.89)
SNAP		-0.0753			-0.0618
		(0.0502)			(0.0516)
TANF			-0.170		-0.133
			(0.101)		(0.111)
Med				-0.124	-0.0299
				(0.0945)	(0.106)
_Cons	27.55***	21.34***	24.07***	24.67***	27.50***
	(4.965)	(2.996)	(4.19)	(5.686)	(5.598)
X^2	6.74*	4.24	4.86	3.71	7.16
R^2	0.0756	0.0524	0.0573	0.0490	0.0787

Note. $N = 128$. MMR = maternal mortality ratio. Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.15

Results for Extended White Maternal Mortality, Revised States Only

	(1)	(2)	(3)	(4)	(5)
	MMR	MMR	MMR	MMR	MMR
Generosity	-0.383*				
	(0.113)				
High BMI	1.827**	1.740**	1.650**	1.327*	1.878**
	(0.564)	(0.659)	(0.528)	(0.584)	(0.64)
SNAP		-0.0826			-0.0678
		(0.0953)			(0.0972)
TANF			-0.567**		-0.574**
			(0.18)		(0.218)
Medicaid				-0.267	0.051
				(0.194)	(0.218)
_Cons	4.941	-7.782	11.13	13.02	6.746
	(14.94)	(14.90)	(14.55)	(20.34)	(19.78)
X^2	12.44**	7.12*	18.60***	8.94*	20.15***
R^2	0.1733	0.1157	0.2109	0.1425	0.2203

Note. $N = 128$. BMI = body mass index; MMR = maternal mortality ratio; SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.16

Results for Limited White Maternal Mortality, Revised States Only

	(1)	(2)	(3)	(4)	(5)
	MMR	MMR	MMR	MMR	MMR
Generosity	-0.345**				
	(0.0979)				
SNAP		-0.121*			-0.100*
		(0.0504)			(0.0497)
TANF			-0.290**		-0.212
			(0.112)		(0.115)
Medicaid				-0.221*	-0.0714
				(0.102)	(0.11)
_Cons	34.39***	23.76***	27.65***	29.41***	34.69***
	(5.144)	(3.206)	(4.407)	(5.994)	(5.772)
X^2	12.41***	5.74*	6.72**	4.71*	13.25**
R^2	0.1230	0.0612	0.0705	0.0646	0.01281

Note. $N = 128$. MMR = maternal mortality ratio; SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.17

Results for Extended Black Maternal Mortality, Revised States Only

	(1)	(2)	(3)	(4)	(5)
	MMR	MMR	MMR	MMR	MMR
Generosity	0.965**				
	(0.352)				
High BMI	1.161	0.875	1.625	2.949**	2.702*
	(0.901)	(1.186)	(0.983)	(0.936)	(1.141)
SNAP		0.274			0.037
		(0.207)			(0.20)
TANF			0.902*		0.175
			(0.383)		(0.381)
Medicaid				1.068***	0.932*
				(0.285)	(0.396)
_Cons	-20.58	21.09	-15.08	-78.33*	-72.86
	(29.6)	(27.34)	(30.31)	(36.64)	(38.9)
X^2	9.37**	4.08	7.71*	15.47***	15.18***
R^2	0.1441	0.0283	0.1018	0.1990	0.2000

Note. $N = 72$. MMR = maternal mortality ratio; SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.18

Results for Limited Black Maternal Mortality, Revised States Only

	(1)	(2)	(3)	(4)	(5)
	MMR	MMR	MMR	MMR	MMR
Generosity	0.984***				
	(0.274)				
SNAP		0.267			0.223
		(0.154)			(0.148)
TANF			0.813**		0.398
			(0.295)		(0.315)
Medicaid				0.628**	0.417
				(0.221)	(0.26)
_Cons	-8.522	27.28**	13.25	6.738	-9.828
	(14.9)	(10.4)	(11.65)	(13.46)	(15.34)
X^2	12.88***	3.01	7.58**	8.06**	14.02**
R^2	0.1846	0.0379	0.1275	0.1386	0.1948

Note. $N = 72$. MMR = maternal mortality ratio; SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families. Standard errors in parentheses.

* *p* 0 .05, ** $p < 0.01$, *** $p < 0.001$

Section 3.5 Discussion

The first noteworthy result from my analysis is that the models fitted are not replicas of Nelson et al.'s (2018) models; many of the determinants they found to be statistically significant in their analysis were insignificant in my own. A possible reason for this change might stem from my inclusion of ICD-10 codes O96–O97, which means that deaths that are not "pregnancy-caused" but might instead be classified as "pregnancy-associated" or "pregnancy-related" (e.g., overdose, homicide or suicide) are included in my mortality ratios when they are often excluded from traditional maternal mortality analyses despite evidence that these causes might account for as many deaths as traditional obstetric causes (Clark, 2012; Creanga et al., 2014; Goldman-Mellor & Margerison, 2019). Additionally, Nelson et al. (2018) used a longer panel than my own (1997–2012) so that they might have found effects that my shorter panel could not. Lastly, so much of the variation in the MMR is attributable to the revision of the death certificate; although I generated a variable for each state-year regarding the proportion of their certificates that are revised, Nelson et al. only used a binary indicator for whether the state had adopted the revised certificate by 2011.

What I found in my final models was that generosity overall was only a determinant of mortality for the limited mortality ratio; the same was true of SNAP. For the extended mortality ratio, the only safety net program with a statistically significant effect on mortality was TANF. The direction of the effects is as expected; increasing SNAP or TANF generosity, or increased generosity of the safety net package as a whole, lowers maternal mortality. In none of my models did Medicaid have a statistically significant effect on maternal mortality; this seems hugely counterintuitive, as access to publicly funded healthcare has an effect on public health beyond its role as part of the social safety net; see Figure 3.4 (Chung & Muntaner, 2006). The exception to this is analysis carried out using state residents, rather than occurrences. In one of those models, Medicaid was significantly associated with a reduction in limited maternal mortality for White women (see Table A.3.4).

The fact that Medicaid is almost never significantly associated with reduced mortality might be because its generosity is measured in the same year as the mortality ratios. So much of maternal mortality is dependent on the underlying health of the mother; inasmuch as underlying health depends on coverage and care, it depends not just on access to healthcare when pregnant but on access to quality healthcare throughout her life. Going forward, it might be worthwhile to lag measures of Medicaid in some way, to account for the generosity a woman experienced prior to becoming pregnant. Prior to my analysis, I hypothesized that Medicaid might be a significant determinant of maternal mortality in part because Medicaid is responsible for paying for the majority of births in this country, to say nothing of the fact that it allows low-income expectant mothers access to prenatal care and other obstetric services.

However, the fact that the percentage of births financed by Medicaid does not at all reflect the percentage of women who are covered by the program means that there is likely undercoverage of the population "at risk" of becoming pregnant. Although they may gain access to Medicaid when pregnant or after giving birth, the underlying health status that truly determines mortality risk is fixed prior to this. Eliason (2020) found that Medicaid expansion under the ACA (2010) was associated with significantly reduced maternal mortality. As more women have access to health coverage before becoming pregnant, it is possible that maternal mortality might begin to decrease in a meaningful way.

Another interesting finding is that, for the limited MMR, deaths whose underlying cause of death was coded as obstetric, while the aggregate measure of generosity was significantly associated with a decrease in maternal mortality, the inclusion of each of the three programs on their own showed no statistical significance (Table 3.5). It is clear that the effect of aggregate generosity is not entirely attributable to the significance of SNAP on its own because SNAP's significance disappears when the other two safety net programs are added separately. Additionally, the coefficient on generosity as a whole is nearly 3 times the size of the coefficient on SNAP alone. This result confirms not only the utility of aggregate safety net generosity as a measure, but also the concept of "packages" of social policies or of support (Meyers et al., 2001). The whole of the social safety net is more than the sum of its parts, in this case, generosity is more than the individual effects of the three programs explored.

The effect of generosity is dwarfed by the effects of the determinants included in the baseline model. Together, the proportion of births to Black women and the proportion of death certificates issues that are the 2003 revision account for 24% of the variation in the limited MMR (see Table 3.10); the addition of aggregate generosity explains only an additional 2%. Although generosity is statistically significant, the policy significance is seemingly quite small. However, similar to the way in which the combination of the three programs explored here exacerbated their individual effect, it is possible that the addition of other safety net programs not accounted for in the index could have an even greater effect. The most likely program to have an effect in this way is WIC, which, although it is not included in the index because of a lack of variation, could be considered in analyses that focus on a particular state or a particular time instead of exploiting a panel.

In the results for extended maternal mortality I found that TANF is the only program of statistical significance, whether it is combined with other safety net programs (see Table 3.5). Unlike the case of limited mortality, aggregate generosity is not significant and TANF remains significant on its own even when entered into the model in combination with the other two programs. TANF on its own explains an additional 2% of the variation in extended MMR from the baseline model. A likely reason that TANF affects only extended, rather than limited MMR, is that extended MMR is likely to be picking up more “pregnancy-associated” or “pregnancy-related” deaths relative to limited MMR, which is much more likely to detect “pregnancy-caused” deaths. The former are more likely to occur after labor and delivery relative to the latter. TANF is only available to households with children (although some states do allow women expecting their first child at various points in their pregnancy); therefore, I would speculate that its protective effect comes after discharge from the hospital or birthing facility and so is less likely to protect against more proximate obstetric causes of mortality.

I chose to focus on the Black–White differential because it is of significant public concern, ranking very high on the public’s agenda. Although MMR for American Indian/Alaska Native women is also extremely high compared to White MMR, the numbers are so small and concentrated in so few states that the analysis at the state level would be extremely limited. The MMR for Hispanic women (of all races) is on the whole lower than for non-Hispanic White women, however the range is much wider, with a maximum expanded MMR of 477 deaths per 100,000 live births, whereas the maximum expanded MMR for White women is less than 100 (see Table 3.4). Although I do not explore the Hispanic MMR and therefore, do not discuss reasons for this large variance, much room remains for future analysis of states in which MMRs for Hispanic women are much higher than they are for White women, in contrast to the national trend, and the reasons for it.

In looking at the results of the race-stratified analysis, it is clear that Black maternal mortality is inherently different. Although White maternal mortality reflects the results seen in total mortality, Black MMRs show no effect of the generosity of the safety net despite earlier findings that lower income inequality and expansion of Medicaid are associated with improved Black maternal mortality relative to White women (Eliason, 2020; Vilda et al., 2019). It is clear that the "traditional" risk factors for mortality that Nelson et al. explored cannot explain Black maternal mortality in the way that they can total mortality. Even if those risk factors have explanatory powers at the individual level, when one looks at Black maternal mortality ratios as a whole, there is clearly more determining the rates than has been studied to date. Going forward, unique sources of stress for Black women need to be identified and ideally quantified for inclusion in analysis. Only by targeting the factors that uniquely affect Black mothers is it possible to reduce the enormous racial disparity in maternal deaths.

Looking at the results for only the states that used the revised death certificate throughout the entire period, the results change primarily for the race-stratified analyses. Although the ameliorative effect of safety net generosity on mortality is even more significant for White women, Black mothers show strongly significant negative effects of safety net generosity on maternal mortality; as generosity increases, so too does Black maternal mortality. Although the major reduction in the number of observations used is obviously problematic, especially when looking at Black MMRs, this result further confirms that the nature of Black maternal mortality is fundamentally different from White maternal mortality, and this distinction should be explored further.

The most important thing to consider, in looking at the results that show no major ameliorative effect of generosity on maternal mortality, is what the metric of generosity is actually measuring. The results of these analyses should not be seen to prove that increasing assistance through programs similar to Medicaid will not have a positive effect on maternal mortality: researchers know that is not true, that expanding these programs can improve maternal birth outcomes. What my generosity score actually measures is the statutory and regulatory hurdles to accessing assistance. Rather than interpreting the results to mean that increasing this access does not have an entirely positive effect on MMRs, it is instead possible that the previously demonstrated impact of these programs occurs because of something besides their regulations and procedures. My measure does not contain indicators of how many people receive assistance, how much assistance they typically receive, and what form that assistance takes.

Therefore, it would perhaps be more accurate, to describe the index as a measure of the accessibility of the safety net, rather than its generosity. Medicaid accessibility is not significantly associated with a reduction in maternal mortality, which means that other facets of the program are significantly associated. Medicaid expansion, following the ACA (2010), has demonstrated marked improvements in maternal mortality, especially for Black women; nevertheless, the index does not demonstrate a similar effect; therefore, a piece is missing in this index (Eliason, 2020). Going forward, it behooves researchers to examine specifically what parts of increased "generosity" are responsible for the improved outcomes: Is it the provision of resources or services? Is it eligibility criteria? Perhaps, future analysists should look at the subindices and their individual effects on MMRs.

Although the purpose of creating the index was to generate a parsimonious measure of the safety net, a single generosity figure precludes me from knowing what is most directly responsible for MMR reductions. However, my results also show that breaking the safety net apart into its component pieces does not demonstrate the same effect as the combination of the programs. I would propose, going forward, that program subindices for various characteristics of the programs be combined into characteristic subindices that contain all three programs. In this way, it would be possible to examine whether eligibility criteria for all three programs might contribute to reduced mortality, or to examine the administrative regulations, rather than looking at all aspects of the programs at once.

Additionally, if the index is in fact measuring accessibility rather than generosity, the benefits of easier access might accrue to those who are relatively better off regarding their social capital or experiences with bureaucracy. Again, the index is a measure of the rules as they are written, not as they are enforced. If eligibility is extended or requirements eliminated, it is unlikely that the average citizen and most importantly someone already fighting the stresses of poverty would know about these changes or how to take advantage of them, which means that the benefits of the increased accessibility accrue to the potential recipients who are relatively socially advantaged. In the United States, those benefits are then likelier to accrue to White women, while Black women are likely to remain at a disadvantage.

Although Black maternal mortality that seems to increase with the accessibility or generosity of the safety net is extremely concerning, I do not understand it to mean that increasing access to the programs actually has a negative impact on Black maternal health. Rather, clearly important variables are omitted from my analysis. Although my selection of control variables was inspired by prior research, too much of that research has focused on individual-level determinants of mortality, even if those individual determinants were measured at the state level. For example, Nelson et al. (2018) claimed to focus on state-level factors, but many of their explanatory variables are actually measures of how common the individual-level risk factors are in a given state. Although these factors are important, they are not truly reaching the social determinants of maternal health.

In fact, examining the effect of generosity or accessibility of the safety net without other indicators that truly measure the social and policy determinants of maternal mortality is possible, but is also incomplete. The next steps are to continue searching for the social factors and to include them in the analysis, examining factors like income inequality and measures of racial equality, which Vilda et al. (2019) have demonstrated are associated with maternal mortality.

Conclusion

The relatively high rate of maternal death in the United States is largely socially determined. Although analyses to date have focused on individuals and analyzing individual level data, they have clearly identified risk factors that are known to be the result of socioeconomic status, societal organization, and the public provision of social and health assistance in addition to individual and clinical factors. However, attempts to determine the relative influence of those social determinants on aggregate rates has been seriously lacking to date. The few analyses using state-level data have largely failed to isolate the effect of public social policy.

The analysis carried out in this paper uniquely highlights the role of the social safety net in ameliorating the abysmal maternal death rates in the United States. Notably, it identifies the combination of social programs into a package of support as offering a protective effect beyond any individual program effect. Yet one of the most concerning features of the maternal mortality crisis is its enormous racial gap, and yet I find no evidence that these policies affect Black mothers the way they seem to affect White mothers. Although the generosity index is a worthwhile measure of how wide the social safety net is cast, for Black women there is a fundamental disconnect from the supportive effects of that net.

As the maternal health crisis continues to climb the policy agenda—gaining more attention and action from legislators, clinicians, public health experts and the public—it will be necessary to refine any generosity measure so that it accurately reflects the experiences of all Americans. As discussed in the first paper, the welfare rules database (Urban Institute, n.d.) used in these papers only included formal policies and decisions as written by state and federal agencies. The database (and consequently the generosity index) cannot account for how the individuals responsible actually administer these programs. Black Americans experience a different daily reality from most other Americans; therefore, one can expect that they also experience a different system of public support or the social safety net. Future analysis needs to be guided by the acknowledgement of this dual society and by attempt to include information from both groups of Americas: Americans whose experience is felt by most individuals, and Americans whose experience is felt by Black individuals.

Going forward, I hope that researchers can finally disentangle the variation in mortality ratios from the variation in the sensitivity of measurement. The enormous effect of the 2003 revision to death certificates will ideally disappear now that all states have adopted the revised version. The growing calls for MMRCs, as well, will help to identify sensitively and accurately maternal deaths. When accurate MMRs exist for all states, the exploration of population-level factors and policy decisions will allow a more nuanced understanding of the social determinants of maternal deaths, and subsequently how they might differ by race.

CONCLUSION

The three papers that comprise this manuscript represent my attempt to examine the role of safety net generosity on a public health outcome of grave concern, the maternal mortality rate in the United States. The initial impetus was to find a way of establishing a quantitative measure of social assistance across states and time. In the first paper, I explain the process whereby assistance programs were selected and how their rules were then quantified. In the second paper, I then address how to combine program features into a single measure, using those quantified rules from the first paper to create a simple index by averaging together the scores for each state in each year. Although I attempted a factor analysis, my hypothesized models failed to explain adequately the data patterns. Finally, in the third paper, I demonstrate how the index might be used in public health analysis by incorporating the generosity index into state-level analysis of maternal mortality.

What is unique about this combination of papers is that I attempt to bridge the gap between public health and policy analysis. Although the first two papers fall very much in the tradition of political science or sociology to use different techniques to combine data in novel ways and create unique measures, the third paper is a very traditional public health analysis of state-level factors associated with maternal mortality. The latter category of research too often uses only direct measures of relevant factors. Even researchers who have examined the social determinants of population health have used indicators of social factors that are not constructed, but are observable. However, in as the fields of education, psychology, and political science, researchers frequently construct more sophisticated indicators to illuminate an underlying concept.

The three papers contained in this manuscript borrow from both traditions, first because I constructed a generosity measure, and second because I used it in a broader analysis. Although the current best measure of generosity is the naïve index, obtained by averaging all observed indicators, going forward, I hope that it will be possible to refine this measure by using the additional technique of weighting the observed indicators by their relative theoretical importance. I also hope that my use of a constructed measure of a latent characteristic (e.g., "generosity" or "accessibility" of the social safety net in a public health analysis) will not remain a rare instance of public health and policy research using constructed indicators, and that other researchers will seek to operationalize latent characteristics for use in their analyses.

In addition to bridging the divide between methodological social science and health policy analysis, in my third paper, I fill a large gap in the literature on maternal mortality in the United States. However, even as the maternal health crisis gains national and international attention, sparking increased research on the topic, scholars have focused almost exclusively on individual-level and facility-level analyses. Very few studies have used population-wide, state-level factors to examine maternal health. How can Americans solve a problem affecting their entire society without first understanding the society-wide factors that influence it?

The final major contribution of these papers is that I found that, regarding the social safety net, the whole is greater than the sum of its parts. Although the piecemeal inclusion of the three safety net programs that I used in my analysis demonstrated limited or no effect on maternal mortality, the combination of the three programs into an index does appear to have an effect. This finding demonstrates the value of the work performed in Papers 1 and 2; although traditional models might include the programs as individual measures, the combination of programs that I generated in the first two papers showed the actual effect on the outcome. By carrying out the analysis in Paper 3 using the index generated in Papers 1 and 2, I was able to observe an effect that would otherwise have been missed.

This result also indicates valuable value regarding the safety net itself. Social assistance and its effect on maternal health can be understood as the proverbial three-legged stool: when one piece or program is taken away, the stool or the buffer of social assistance falls, or fails to support people as intended. This has important policy implications, for shrinking one aspect of social assistance is also akin to severing or removing a strand from the fabric of the social safety net: many more people are going to fall through the holes in the fabric. Even if the target program or policy seems unrelated to an outcome of interest, it remains necessary for the other policies or programs—that do theoretically relate to that outcome—to have an effect.

Ultimately, I imagine that additional filaments make up the social safety net and that, when they are combined with the programs in my index, they could have an even greater combined impact. Performing an analysis using the measures of these supports on their own might fail to yield an observed effect in the same way that a single strand of fiber cannot support a person. Furthermore, even multiple supports or strands might allow people to fall through the fabric if the net is woven too loosely; therefore, it is only by weaving numerous strands into a durable net that people can truly be supported. If the generated construct of latent generosity is the safety net, then one hopes that adding additional forms of social support to that measure in the future will provide a more robust observed effect of that support. These three papers are only the beginning, but I hope that this idea of the safety net as a metaphorical physical net—that only works well when all of its strands are woven well—is incorporated into future research on social assistance.

APPENDIX 1: FACTOR ANALYSIS VARIABLE LIST

Supplemental Nutrition Assistance Program (SNAP)

Data regarding the food stamp program come from the SNAP Policy Database (USDA, ERS, n.d.). The database contains observations from all 50 states and Washington, D.C. for the years 1996–2016. Observations are recorded monthly.

FS01 / SNAP_bbce: a categorical variable indicating whether a state allows broad-based categorical eligibility (BBCE). As data is collapsed to generate a year from 12 months of observations, this variable can detect years in which BBCE was allowed in some months but not in others. This variable takes on a value of 2 if the state allowed BBCE for the entire year (n = 367), a value of 1 if BBCE was allowed in only part of the year (n = 39), and it takes on a value of 0 if the state did not allow BBCE at all during the year (n = 665).

FS02 / SNAP_cap: a categorical variable indicating whether a state operates a combined application project (CAP). As data is collapsed to generate a year from 12 months of observations, this variable can detect years in which CAP was allowed in some months but not in others. This variable takes on a value of 2 if the state operated CAP for the entire year (n = 189), a value of 1 if CAP was in use for only part of the year (n = 18), and it takes on a value of 0 if the state did not operate CAP at all during the year (n = 864).

FS03 / SNAP_ebtissuance: a continuous variable indicating the proportion of a state's SNAP expenditures that were spent using Electronic Benefit Transfer. This variable takes the proportion of state SNAP benefits accounted for by EBT in each month and finds the average of this figure for all 12 months.

FS04 / SNAP_faceini: a categorical variable indicating whether a state has been granted a waiver to use telephone interviews instead of face-to-face interviews at initial certification in at least part of the state. This variable takes on a value of 0 if the state had not been granted a waiver (*n* = 698), a value of 1 if a state had this waiver for some but not all of the year (*n* = 52) and a value of 2 if the state had this waiver in place for the entire year (*n* = 321).

FS05 / SNAP_facerec: a categorical variable indicating whether a state has been granted a waiver to use telephone interviews instead of face-to-face interviews at recertification in at least part of the state. This variable takes on a value of 0 if the state had not been granted a waiver (*n* = 614), a value of 1 if a state had this waiver for some but not all of the year (*n* = 50) and a value of 2 if the state had this waiver in place for the entire year (*n* = 407).

FS06 / SNAP_reportsimple: a categorical variable indicating whether a state uses the simplified reporting option for houses with earnings. This variable takes on a value of 0 if the state does not use simplified reporting (*n* = 377), a value of 1 if a state uses it for some but not all of the year (*n* = 46) and a value of 2 if the state uses it for the entire year (*n* = 648).

FS07 / SNAP_vehicle: a categorical variable indicating to what degree the state excludes vehicles from the asset limit. This variable takes on a value of 2 if the state excludes all vehicles from the asset test (*n* = 442). It takes on a value of 1 if the state exempts at least one but not all of the vehicles in a household from the asset test (under both traditional and BBCE), or if it exempts a value greater than the SNAP standard exemption from the fair market value of a vehicle for counting in the asset test (*n* = 255). It takes on a value of 0 if it does not exempt one or all vehicles (*n* = 374). Currently the values range from 0–2 because of the data collapse over the year. Data was not available for 2016, so the assumption was made that no change occurred since 2015, and the value remains the same.

FS08 / SNAP_noncit: a continuous variable indicating the coverage of noncitizens who are permitted assistance under federal law. This variable is created by finding the average of the monthly observations of three categorical variables measuring whether there is full or partial coverage of allowed noncitizen adults, noncitizen children and noncitizen elderly individuals. These three values were then averaged to find a variable ranging from 0–2 that provides some indication of a state-year's coverage of noncitizens.

FS09 / SNAP_certavg: a continuous variable that measures the length of the average certification period in months, where approximately 5.5 is the shortest period and the longest period is almost 25.5 months. These data are generated by taking the average certification period in months for earning, nonearning and elderly households. This value is then collapsed from 12 months to one yearly observation. A longer certification period indicates more generosity as it means the household has to recertify their eligibility less often.

FS10 / SNAP_call_centers: a categorical variable indicating whether the state operates call centers. This variable takes on a value of 2 if the state operated call centers state-wide for the entire year (n = 236). It takes on a value of 1 if it operated call centers in some parts of the state or for some part of the year (either statewide or in part of the state; indicates partial coverage) (n = 180). It takes on a value of 0 if the state did not operate any call centers (n = 655).

FS11 / SNAP_finterprint: a categorical variable indicating whether the state requires finger-printing of applicants. This variable takes on a value of 0 if the state required finger-printing in any part of the state at any time during that year (*n* = 77), and a value of 1 if the state did not require finger-printing at all (*n* = 994).

FS12 / SNAP_online: a categorical variable indicating whether the state allows online applications. This variable takes on a value of 2 if the state allowed online applications across the entire state for the entire year (*n* = 312). It takes on a value of 1 if it allowed online applications in some parts of the state or for some part of the year (either statewide or in part of the state; indicates partial coverage) (*n* = 66). It takes on a value of 0 if the state did not allow online applications (*n* = 693).

FS13 / SNAP_outreach: a binary variable indicating whether the state spent any money in a year (whether that money comes from the state, federal government or a grant) on outreach. This variable takes on a value of 1 if the state spent any money that year (*n* = 635) and takes on a value of 0 if the state had no outreach spending (*n* = 436).

FS14 / SNAP_transition: a categorical variable indicating whether the state offers transitional benefits to those leaving SNAP. This variable takes on a value of 2 if the state offered transitional benefits for the entire year (*n* = 236), a value of 1 if the state offered them for part of the year (*n* = 26), and a value of 0 if it did not offer them at all (*n* = 809).

Temporary Assistance for Needy Families (TANF)

Data on state TANF policies come from the Urban Institute's (n.d.). Welfare Rules Database, which contains information on TANF policies in all 50 states and Washington, D.C. for the years 1999–2016 and are recorded based on the state's TANF policy manual for that year. In states where policies can vary even within the state, the policy that is used for most of the state or in the most populous jurisdiction is recorded.

TANFD1 / TANF_divert_1: a binary program indicating whether a state has a diversion program. This variable takes on a value of 0 if the state does have a diversion program (*n* = 557) and a value of 1 if it does not have a diversion program (*n* = 361). The existence of a diversion program is thought to be an indicator of less generosity because it is intended to keep people off of the welfare rolls.

TANFD3 / TANF_divert_3: a categorical variable indicating what forms diversion payments take, if the state does have a diversion program. This variable takes on a value of 0 if the diversion payment is a cash loan that must be paid back (*n* = 36). It has a value of 1 if diversion assistance is only rendered through support services (*n* = 1), a value of 2 if it consists of support services and vendor payments but does not include cash (*n* = 62), a value of 3 if it gives support services, vendor payments and allows for the possibility of cash assistance (*n* = 155), and it takes on a value of 4 if diversion assistance is given as a cash payment, although this can include vendor payments as well (*n* = 302).

TANFD5 / TANF_divert_5: a binary variable that indicates whether, in states that have a diversion program, there exists a time period after diversion during which the unit is ineligible for further TANF assistance. This variable takes on a value of 1 if there is no period of ineligibility (*n* = 116) and a value of 0 if there is such a period (*n* = 278).

TANFD6 / TANF_divert_6: a categorical variable indicating whether receipt of diversion assistance counts towards the lifetime limit. This variable takes on a value of 2 if the time does not count (*n* = 463), 1 if it varies (*n* = 35), or 0 if it does count (*n* = 56).

TANFJS / TANF_jobsearch: a binary variable indicating whether the state requires a job search upon application. This variable takes on a value of 0 if the states requires a job search (*n* = 332) and a value of 1 if no job search is required (*n* = 584).

TANFPREG / TANF_pregnant: a categorical variable that indicates in which trimester of pregnancy, if any, a woman with no other children becomes eligible for assistance. This variable takes on the value of 0 if pregnant women with no other children are never eligible, 1 if they are eligible in the 3rd trimester (n = 200), 2 if eligible in the 2nd trimester (n = 209) and 3 if eligible in the 1st trimester or upon verification of the pregnancy (n = 169).

TANFTEEN / TANF_teenhead_1: a binary variable that indicates whether teenagers can ever be considered unit heads. PRWORA mandated that states cannot provide assistance to teen parents not living with a parent or guardian unless they meet certain characteristics that would make doing so impossible/against their interest (Saxon, 1997). This variable takes on a value of 0 if teens cannot be considered unit heads (n = 178) or 1 if they can be unit heads (n = 733).

TANFA1 / TANF_asset_1: a categorical variable indicating what the initial asset limit is for *applicants*. This variable takes on a value of 1 for asset limits up to \$1000 (n = 181), a value of 2 for limits above \$1000 and up to \$2000 (n = 397), a value of 3 for limits above \$2000 up to \$3000 (n = 198), a value of 4 for limits above \$3000 and up to \$6000 (n = 61) and a value of 5 for a limit above \$6000 or in cases where the asset test has been eliminated (n = 75).

TANFINC1 / TANF_income_1: a categorical variable indicating the initial income eligibility limit for *applicants*. This variable takes on a value of 1 for income limits up to \$500 (n = 202), a value of 2 for limits above \$500 up to \$1000 (n = 480), a value of 3 for limits above \$1000 and up to \$1500 (n = 188) and a value of 4 for income limits greater than \$1500 (n = 34).

TANFBN5 / TANF_benefit_5: a categorical variable indicating the statutory maximum benefit for a family of three. This variable only has 177 observations, likely to be eliminated from the dataset.

TANFBN6 / TANF_benefit_6: a categorical variable indicating the maximum monthly benefits for a family of three. This variable takes on a value of 1 for benefits up to $200 (*n* = 39), a value of 2 for benefits above $200 and up to $300 (*n* = 203), a value of 3 for benefits above $300 and up to $400 (*n* = 183) , a value of 4 for benefits above $400 and up to $600 (*n* = 352), and a value of 5 for benefits greater than $600 (*n* = 83).

TANFBV1 / TANF_behavior_1: a binary variable indicating whether the state requires school attendance from children receiving assistance. This variable takes on a value of 0 if there are school requirements (*n* = 623) and a value of 1 if there are no school requirements (*n* = 294).

TANFBV2 / TANF_behavior_2: a binary variable indicating whether the state has school bonuses. This variable takes on a value of 0 for states that do provide school bonuses (*n* = 148) and a value of 1 if they do not (*n* = 769). Despite offering a "bonus" we decided to code those states that offer this incentive as less generous because it still represents a condition/incentive for recipients to meet in order to "unlock" particular levels of assistance. The more generous condition is actually to provide unconditional assistance.

TANFBV3 / TANF_behavior_3: a binary variable indicating whether the state has immunization requirements. This variable takes on a value of 0 if there are immunization requirements (*n* = 466) and a value of 1 if there are not immunization requirements (*n* = 451).

TANFBV4 / TANF_behavior_4: a binary variable indicating whether the state has health screening requirements. This variable takes on a value of 0 if there are health screening requirements (*n* = 126) and a value of 1 if there are not health screening requirements (*n* = 791).

TANFBV5 / TANF_behavior_5: a binary variable indicating whether the state has other requirements. This variable takes on a value of 0 if there are other requirements (*n* = 11) and a value of 1 if there are no other requirements (*n* = 498).

TANFBV0 / TANF_behavior_0: a categorical variable indicating how many conditions a state puts on recipients. This variable takes on a value of 0 if there are five or more conditions (*n* = 121), a value of 1 if there are four conditions (*n* = 218), a value of 2 if there are three conditions (*n* = 272), a value of 3 if there are two conditions (*n* = 218), a value of 4 if there is only one condition (*n* = 74) and a value of 5 if there are no conditions or incentives (*n* = 15).

TANFWX1 / TANF_workex_1: a continuous variable that indicates how many hours a single-unit head must work in an uncompensated job to be exempted from work requirements. This variable was generated by subtracting the number of hours from 50, so that as the number of hours needed to be worked for an exemption increased, this variable score decreases. The exception is scores of zero, which remained as such, because they represent states that do not exempt unit heads who work in uncompensated jobs from work requirements.

TANFWX2 / TANF_workex_2: a binary variable that indicates whether a state exempts a single-unit head who is ill or incapacitated from work requirements. This variable takes on a value of 0 if unit heads are not exempted for illness/incapacity (*n* = 320) and a value of 1 if they are exempted (*n* = 526).

TANFWX3 / TANF_workex_3: a binary variable that indicates whether a state exempts a single-unit head who is caring for someone ill or incapacitated from work requirements. This variable takes on a value of 0 if unit heads are not exempted (n = 212) and a value of 1 if they are exempted (n = 634).

TANFWX4 / TANF_workex_4: a binary variable indicating whether a state exempts single-unit heads who are above a certain age from work requirements. This variable takes on a value of 1 if the state does exempt unit heads who are above a certain age threshold (n = 526) and 0 if it does not (n = 392).

TANFWX5 / TANF_workex_5: a categorical variable indicating the month in which a pregnant single-unit head can be exempted from work requirements. This variable takes on a value of 0 if the pregnant unit head is never exempt (n = 616), a value of 1 if they are exempt in the 3rd trimester (n = 149), a value of 2 if they are exempt in the 2nd trimester (n = 62) and a value of 3 if they are exempt in the 1st trimester or upon verification of the pregnancy (n = 13).

TANFWX6 / TANF_workex_6: a continuous variable indicating the maximum age in months of a child for whose care a single-unit head is exempted from work requirements.

TANFWX0 / TANF_workex_0: a categorical variable indicating how many exemptions the state has from the work requirements for the single head of an assistance unit, ranging from no exemptions to 6 exemptions.

TANFWR1 / TANF_workreq_1: a categorical variable indicating when a single-unit head must begin participation in the work requirements. This variable takes on a value of 0 if they must begin immediately upon application (n = 621), a value of 1 if they must begin after their assessment (*n* = 47), a value of 2 if they must begin within three months (*n* = 39) and a value of 3 if they must begin within two years (*n* = 54).

TANFSC3 / TANF_sanction_3: a categorical variable indicating the most severe sanction possible for failure to comply with requirements. This variable takes on a value of 0 if the penalty is closure of the entire case (*n* = 278), a value of 1 if the unit loses their entire benefit (*n* = 403) and a value of 2 if the unit loses only the adult portion of the benefit (*n* = 119).

TANF2PAR / TANF_two-parent: a categorical variable indicating whether two-parent households are eligible for assistance. This variable takes on a value of 0 if they are never eligible (*n* = 29), 1 if they are eligible but with restrictions (*n* = 200), and 2 if they are eligible without restrictions (*n* = 688).

TANFA4 / TANF_asset_4: a categorical variable indicating the asset limit for recipients (different from initial applicants). This variable takes on a value of 1 if the recipient asset limit is anything up to $2000 (*n* = 143), a value of 2 if the recipient asset limit is $2000 or greater, up to $3000 (*n* = 455), a value of 3 if the limit is $3000 or greater, up to $4000 (*n* = 125), a value of 4 if the limit is $4000 or greater, up to $6000 (*n* = 94), and a value of 5 if the asset limit is $6000 or higher, or the recipient asset limit has been eliminated (*n* = 78).

TANFF1 / TANF_family_1: a binary variable indicating whether a state has a family cap policy (does not increase TANF payments with the birth of an additional child while on TANF). This variable takes on a value of 0 if the state does implement a family cap (*n* = 343), and a value of 1 if they do not have this policy (*n* = 574).

TANFL1 / TANF_limit_1: a binary variable indicating how long the state's lifetime limit is. This variable takes on a value of 0 if the limit is less than 60 months (*n* = 169), and a value of 1 if the limit is 60 months or greater (*n* = 580). There seems to be a problem with this variable, review.

TANFL2 / TANF_limit_2: a binary variable indicating whose benefits are terminated once the lifetime limit is reached. This variable takes on a value of 0 if benefits are terminated for the entire unit (*n* = 783) and a value of 1 if only the adult portion of the benefits are terminated (*n* = 60).

TANFL3 / TANF_limit_3: a binary variable indicating whether the state has spell limits. Spell limits constrain the number of consecutive months a unit can receive assistance. This limit will be shorter than the lifetime limit, and require a period of months without assistance before the unit can reapply (assuming they have not maxed out their lifetime limit). This variable takes on a value of 0 if there are spell limits (*n* = 645), and a value of 1 if the state does not have these limits (*n* = 124).

TANFIM2 / TANF_immigrant_2: This variable seems to present a problem.

TANFIM0 / TANF_immigrant_0: a binary variable indicating whether the state provides assistance to authorized immigrants beyond what is required by PRWORA. This variable takes on a value of 0 if the state does not provide additional assistance (*n* = 462), and a value of 1 if they provide more assistance than required (*n* = 456).

TANFA2 / TANF_asset_2: a binary variable indicating whether the applicant asset limit is higher for households that contain an elderly and/or disabled member. This variable takes on a value of 0 if the initial asset limit for applicants is not increased for units with elderly and/or disabled members (*n* = 778) and a value of 1 if the limit is higher (*n* = 135).

TANFA5 / TANF_asset_5: binary variable indicating whether the recipient asset limit is higher for households that contain an elderly and/or disabled member. This variable takes on a value of 0 if the asset limit for recipients is not increased for units with elderly and/or disabled members (*n* = 761) and a value of 1 if the limit is higher (*n* = 135).

MEDICAID

Data on Medicaid comes from the Henry J. Kaiser Family Foundation and the Urban Institute. Medicaid data is available for all 50 states and Washington, D.C. for the years 2001–2016.

MCEL01 / WG_Medicaid_Eligibility_01: a continuous variable indicating the income eligibility level for children under the age of one as a proportion of the federal poverty line (FPL). This variable ranges from 1.33–4 (indicating eligibility thresholds ranging from 133% FPL to 400% FPL).

MCEL02 / WG_Medicaid_Eligibility_02: a continuous variable indicating the income eligibility level for children between the ages of one and five as a proportion of FPL. This variable ranges from 1.33–4.

MCEL03 / WG_Medicaid_Eligibility_03: a continuous variable indicating the income eligibility level for children between the ages of 6 and 18 years. This variable ranges from 1–4.

MCEL04 / WG_Medicaid_Eligibility_04: a continuous variable indicating the income eligibility level for pregnant women. This variable ranges from 1.33–3.8.

MCEL05 / WG_Medicaid_Eligibility_05: a continuous variable indicating the income eligibility level for parents. This variable ranges from 0.16–2.75.

MCEL06 / WG_Medicaid_Eligibility_06: a continuous variable indicating the income eligibility level for adults without dependents. This variable ranges from 0 for states that do not allow these adults to be eligible for Medicaid, to a maximum of 2.55.

MCAD01 / WG_Medicaid_Admin_01: a continuous variable indicating the average wait length for enrollment.

MCAD02 / WG_Medicaid_Admin_02: a categorical variable indicating whether a state requires a face-to-face interview for enrollment for children. For states with a "state separate program" (SSP), meaning they operate a CHIP program separate from their Medicaid program, the value is an average of the two programs.

MCAD03 / WG_Medicaid_Admin_03: a categorical variable indicating whether a state requires a face-to-face interview for parents. This variable takes on a value of 0 if the state continues to require face-to-face interviews for parents (*n* = 154) and a value of 1 if they have eliminated this requirement (*n* = 756).

MCAD04 / WG_Medicaid_Admin_04: a categorical variable indicating whether a state has eliminated the asset test for all participants. This variable takes on a value of 0 if the state maintains the asset test for all participants (*n* = 24), a value of 1 if they've partially eliminated it (*n* = 55), and a value of 2 if they have eliminated the asset test (*n* = 839).

MCAD05 / WG_Medicaid_Admin_05: a categorical variable indicating whether the state has eliminated the asset test for parents. This variable takes on a value of 0 if the state maintains an asset test for parents (*n* = 354), a value of 1 if either the state separate program (SSP) or the traditional Medicaid program has eliminated the test but not both (*n* = 71), and a value of 2 if the state has eliminated the asset test for parents (*n* = 493).

MCAD06 / WG_Medicaid_Admin_06: a categorical variable indicating whether the state allows for presumptive eligibility in their Medicaid or SSP program. Presumptive eligibility allows for certain individuals, as identified by qualified entities, to begin receiving services before their application is processed Medicaid (n.d.). This variable takes on a value of 0 if the state does not allow presumptive eligibility (*n* = 664), a value of 1 if either the SSP or the traditional Medicaid program allows for presumptive eligibility (*n* = 60), and a value of 2 if the state allows for presumptive eligibility (*n* = 194).

MCAD07 / WG_Medicaid_Admin_07: a binary variable indicating whether pregnant women who are otherwise ineligible are eligible for Medicaid. This variable takes on a value of 0 if the state does not provide coverage for otherwise ineligible pregnant women (*n* = 378) and a value of 1 if the state does provide such coverage (*n* = 540).

MCAD08 / WG_Medicaid_Admin_08: a categorical variable indicating whether the state has continuous eligibility for SSP or Medicaid. Continuous eligibility allows a family to continue receiving Medicaid or SSP coverage for 12 months even if the family's income changes during that year to exceed the eligibility threshold Medicaid (n.d.). This variable takes on a value of 0 if the state does not allow continuous eligibility (*n* = 359), a value of 1 if the state allows continuous eligibility for either SSP or Medicaid program (*n* = 210), and a value of 2 if the state allows continuous eligibility (*n* = 349).

MCAD09 / WG_Medicaid_Admin_09: a categorical variable indicating whether the state has eliminated face-to-face interviews for all enrollees to renew their enrollment in the program. This variable takes on a value of 0 if the state continues to require face-to-face interviews (*n* = 21), a value of 1 if this requirement was eliminated for SSP or Medicaid but not both (*n* = 17), and a value of 2 if the interview requirement has been eliminated (*n* = 880).

MCAD10 / WG_Medicaid_Admin_10: a categorical variable indicating whether the state has eliminated face-to-face interviews for parents to renew their enrollment in the program. This variable takes on a value of 0 if the state continues to require face-to-face interviews (*n* = 105), a value of 1 if this requirement was eliminated for a SSP or Medicaid but not both (*n* = 13), and a value of 2 if the interview requirement has been eliminated (*n* = 800).

MCAD11 / WG_Medicaid_Admin_11: a variable indicating renewal frequency for all participants. This variable can take on a value of 6 (*n* = 43), 6.5 (*n* = 9), 7.5 (*n* = 1), 9 (*n* = 50), 10.5 (*n* = 1) or 12 (*n* = 814).

MCAD12 / WG_Medicaid_Admin_12: a variable indicating renewal frequency for parents. This variable can take on a value of 0.96 (*n* = 9), 3 (*n* = 11), 6 (*n* = 102), 9 (*n* = 38), or 12 (*n* = 758).

MCIM01 / WG_Medicaid_Immigrant_01: a binary variable indicating whether the state provides coverage to lawfully present immigrant children prior to the expiration of the 5-year waiting period, as allowed under the CHIP legislation (Medicaid, n.d.). This variable takes on a value of 0 if immigrant children do not receive coverage during the 5-year ban (*n* = 499) and a value of 1 if the state does provide coverage (*n* = 368).

MCIM02 / WG_Medicaid_Immigrant_02: a binary variable indicating whether the state provides coverage to children in the country unlawfully. This variable takes on a value of 0 if unauthorized immigrant children are ineligible (*n* = 783) and a value of 1 if they are eligible (*n* = 84).

MCIM03 / WG_Medicaid_Immigrant_03: a binary variable indicating whether a state provides coverage to legal permanent residents (LPRs) during the 5-year ineligibility period. This variable takes on a value of 0 if the state does not provide LPRs with this coverage (n = 711) and a value of 1 if LPRs are covered during this time (n = 156).

MCIM04 / WG_Medicaid_Immigrant_04: a binary variable indicating whether the state provides coverage to adults in the country unlawfully. This variable takes on a value of 0 if unauthorized immigrant adults are ineligible (n = 851) and a value of 1 if they are eligible (n = 16).

MCIM05 / WG_Medicaid_Immigrant_05: a binary variable indicating whether the state provides coverage for pregnant women who are LPRs during the 5-year ban. The variable takes on a value of 0 if the state does not provide this coverage (n = 474) and a value of 1 if they do (n = 393).

MCIM06 / WG_Medicaid_Immigrant_06: a binary variable indicating whether a state provides coverage for pregnant women who are in the country unlawfully. This variable takes on a value of 0 if unlawfully present pregnant women are not eligible for coverage (n = 623) and a value of 1 if they are eligible (n = 244).

MCIM07 / WG_Medicaid_Immigrant_07: a binary variable indicating whether a state provides Medicaid to LPRs after the 5-year ban expires. This variable takes on a value of 0 if they do not provide coverage (n = 121) and a value of 1 if they do provide it (n = 746).

MCBOP1: a categorical variable indicating whether the medical/surgical services of a dentist are covered. This variable takes on a value of 0 if the services are not covered (n = 0), a value of 1 if services are covered but require a copay (n = 308), and a value of 2 if the services are covered and do not require a copay (n = 508).

MCBOP2: a categorical variable indicating whether the podiatrist services are covered. This variable takes on a value of 0 if the services are not covered (*n* = 104), a value of 1 if services are covered but require a copay (*n* = 402), and a value of 2 if the services are covered and do not require a copay (*n* = 304).

MCBOP3: a categorical variable indicating whether occupational therapy services are covered. This variable takes on a value of 0 if the services are not covered (*n* = 308), a value of 1 if services are covered but require a copay (*n* = 192), and a value of 2 if the services are covered and do not require a copay (*n* = 316).

MCBOP4: a categorical variable indicating whether physical therapy services are covered. This variable takes on a value of 0 if the services are not covered (*n* = 250), a value of 1 if services are covered but require a copay (*n* = 193), and a value of 2 if the services are covered and do not require a copay (*n* = 373).

MCBOP5: a categorical variable indicating whether eyeglasses and other visual aids are covered. This variable takes on a value of 0 if they are not covered (*n* = 138), a value of 1 if they are covered but require a copay (*n* = 226), and a value of 2 if they are covered and do not require a copay (*n* = 452).

MCBOP6: a categorical variable indicating whether dental services are covered. This variable takes on a value of 0 if the services are not covered (*n* = 79), a value of 1 if services are covered but require a copay (*n* = 334), and a value of 2 if the services are covered and do not require a copay (*n* = 403).

MCBOP7: a categorical variable indicating whether prosthetic and orthotic devices are covered. This variable takes on a value of 0 if they are not covered (*n* = 26), a value of 1 if they are covered but require a copay (*n* = 184), and a value of 2 if they are covered and do not require a copay (*n* = 606).

MCBOP8: a categorical variable indicating whether services in institutions for mental diseases for those 65 and older are covered. This variable takes on a value of 0 if the services are not covered (*n* = 94), a value of 1 if services are covered but require a copay (*n* = 37), and a value of 2 if the services are covered and do not require a copay (*n* = 685).

MCBOP9: a categorical variable indicating whether target case management services are covered. This variable takes on a value of 0 if the services are not covered (*n* = 36), a value of 1 if services are covered but require a copay (*n* = 15), and a value of 2 if the services are covered and do not require a copay (*n* = 765).

MCBOP10: a categorical variable indicating whether hearing aids and other hearing devices are covered. This variable takes on a value of 0 if they are not covered (*n* = 303), a value of 1 if they are covered but require a copay (*n* = 130), and a value of 2 if they are covered and do not require a copay (*n* = 383).

MCBOP11: a categorical variable indicating whether chiropractic services are covered. This variable takes on a value of 0 if the services are not covered (*n* = 401), a value of 1 if services are covered but require a copay (*n* = 263), and a value of 2 if the services are covered and do not require a copay (*n* = 152).

MCBOP12: a categorical variable indicating whether psychological services are covered. This variable takes on a value of 0 if the services are not covered (*n* = 269), a value of 1 if services are covered but require a copay (*n* = 198), and a value of 2 if the services are covered and do not require a copay (*n* = 349).

MCBOP13: a categorical variable indicating whether hospice care is covered. This variable takes on a value of 0 if it is not covered (*n* = 179), a value of 1 if it is covered but require a copay (*n* = 60), and a value of 2 if it is covered and do not require a copay (*n* = 577).

MCBOP14: a categorical variable indicating whether dentures are covered. This variable takes on a value of 0 if they are not covered (*n* = 295), a value of 1 if they are covered but require a copay (*n* = 123), and a value of 2 if they are covered and do not require a copay (*n* = 398).

MCBOP15: a categorical variable indicating whether rehabilitation services for mental health and substance use are covered. This variable takes on a value of 0 if the services are not covered (*n* = 31), a value of 1 if services are covered but require a copay (*n* = 178), and a value of 2 if the services are covered and do not require a copay (*n* = 607).

MCBOP16: a categorical variable indicating whether nurse practitioner services are covered. This variable takes on a value of 0 if the services are not covered (*n* = 7), a value of 1 if services are covered but require a copay (*n* = 361), and a value of 2 if the services are covered and do not require a copay (*n* = 448).

MCBOP17: a categorical variable indicating whether private duty nursing services are covered. This variable takes on a value of 0 if the services are not covered (*n* = 444), a value of 1 if services are covered but require a copay (*n* = 19), and a value of 2 if the services are covered and do not require a copay (*n* = 353).

MCBOP18: a categorical variable indicating whether services for speech, hearing and language disorders are covered. This variable takes on a value of 0 if the services are not covered (*n* = 262), a value of 1 if services are covered but require a copay (*n* = 200), and a value of 2 if the services are covered and do not require a copay (*n* = 354).

MCBOP19: a categorical variable indicating whether personal care services are covered. This variable takes on a value of 0 if the services are not covered (*n* = 313), a value of 1 if services are covered but require a copay (*n* = 24), and a value of 2 if the services are covered and do not require a copay (*n* = 479).

MCBOP20: a categorical variable indicating whether intermediate care facility services for individuals with intellectual disabilities are covered. This variable takes on a value of 0 if the services are not covered (*n* = 33), a value of 1 if services are covered but require a copay (*n* = 8), and a value of 2 if the services are covered and do not require a copay (*n* = 775).

MCBOP21: a categorical variable indicating whether medical equipment and supplies other than those from home health are covered. This variable takes on a value of 0 if they are not covered (*n* = 10), a value of 1 if they are covered but require a copay (*n* = 258), and a value of 2 if they are covered and do not require a copay (*n* = 548).

MCBOP22: a categorical variable indicating whether optometrist services are covered. This variable takes on a value of 0 if the services are not covered (*n* = 8), a value of 1 if services are covered but require a copay (*n* = 447), and a value of 2 if the services are covered and do not require a copay (*n* = 361).

MCBOPAV: a continuous variable indicating the average of a state-year's values for the variables MCBOP1-MCBOP22. This variable provides information on how many optional benefits a state covers and how well they cover them.

MCMANDA: a categorical variable indicating whether diagnostic screening and preventive services are covered. This variable takes on a value of 0 if the services are not covered (*n*

= 136), a value of 1 if services are covered but require a copay (*n* = 108), and a value of 2 if the services are covered and do not require a copay (*n* = 572).

MCMANDB: a categorical variable indicating whether rural health clinic services are covered. This variable takes on a value of 0 if the services are not covered (*n* = 61), a value of 1 if services are covered but require a copay (*n* = 423), and a value of 2 if the services are covered and do not require a copay (*n* = 332).

MCMAND1: a binary variable indicating whether nurse/midwife services require a copay. This variable takes on a value of 0 if the services do require a copay (*n* = 225), and a value of 1 if they do not have a copay (*n* = 591).

MCMAND2: a binary variable indicating whether outpatient hospital services require a copay. This variable takes on a value of 0 if the services do require a copay (*n* = 544), and a value of 1 if they do not have a copay (*n* = 272).

MCMAND3: a binary variable indicating whether nonemergency medical transportation services require a copay. This variable takes on a value of 0 if the services do require a copay (*n* = 94), and a value of 1 if they do not have a copay (*n* = 722).

MCMAND4: a binary variable indicating whether federally qualified health center services require a copay. This variable takes on a value of 0 if the services do require a copay (*n* = 416), and a value of 1 if they do not have a copay (*n* = 400).

MCMAND5: a binary variable indicating whether nursing facility services other than in institutions for mental diseases require a copay. This variable takes on a value of 0 if the services do require a copay (*n* = 20), and a value of 1 if they do not have a copay (*n* = 796).

MCMAND6: a binary variable indicating whether physician services require a copay. This variable takes on a value of 0 if the services do require a copay (n = 606), and a value of 1 if they do not have a copay (n = 210).

MCMAND7: a binary variable indicating whether inpatient hospital services other than in institutions for mental disease require a copay. This variable takes on a value of 0 if the services do require a copay (n = 437), and a value of 1 if they do not have a copay (n = 379).

MCMAND8: a binary variable indicating whether ambulance services require a copay. This variable takes on a value of 0 if the services do require a copay (n = 127), and a value of 1 if they do not have a copay (n = 689).

MCMAND9: a binary variable indicating whether home health nursing services require a copay. This variable takes on a value of 0 if the services do require a copay (n = 183), and a value of 1 if they do not have a copay (n = 633).

MCMAND10: a binary variable indicating whether laboratory and x-ray services outside of a hospital require a copay. This variable takes on a value of 0 if the services do require a copay (n = 172), and a value of 1 if they do not have a copay (n = 644).

MCMANDCO: a categorical variable indicating how many mandatory services require a copay. A higher number of services that require a copay indicates less generosity; therefore, the numbers are inverted so that a state-year in which all 12 mandatory services require a copay will take on a value of 0 and a state-year in which none of these services require a copay will take on a value of 12.

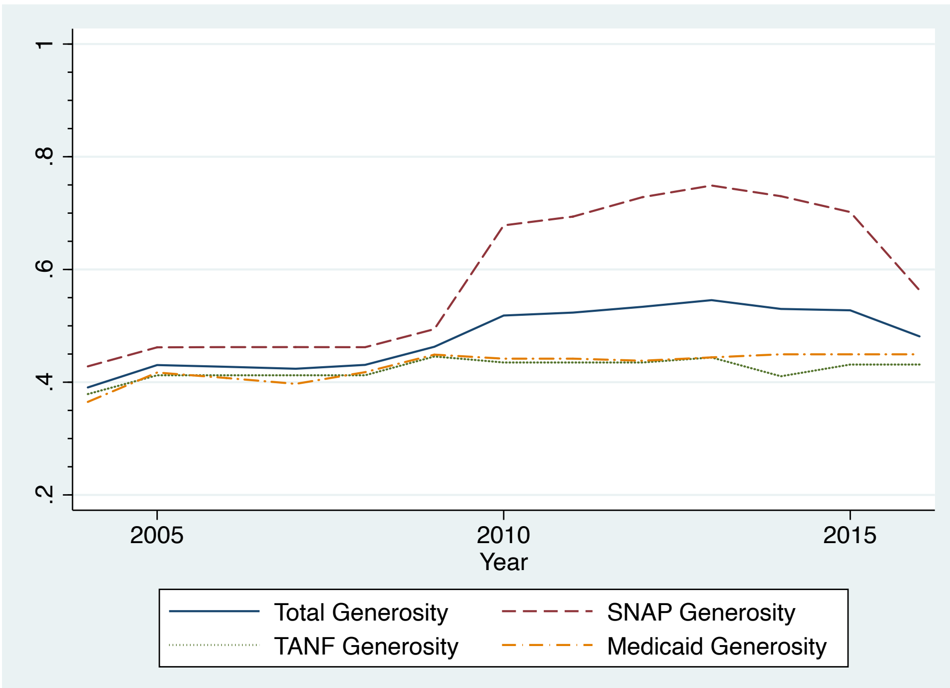
MCRX: a binary variable indicating whether prescription drugs require a copay. This variable takes on a value of 0 if they do require a copay (n = 156), and a value of 1 if there is no copay (n = 660).

APPENDIX 2: NAÏVE INDEX SCORES OVER TIME BY STATE

Figures A.2.1–A.2.51 Total, SNAP, TANF and Medicaid Generosity, 2004–2016

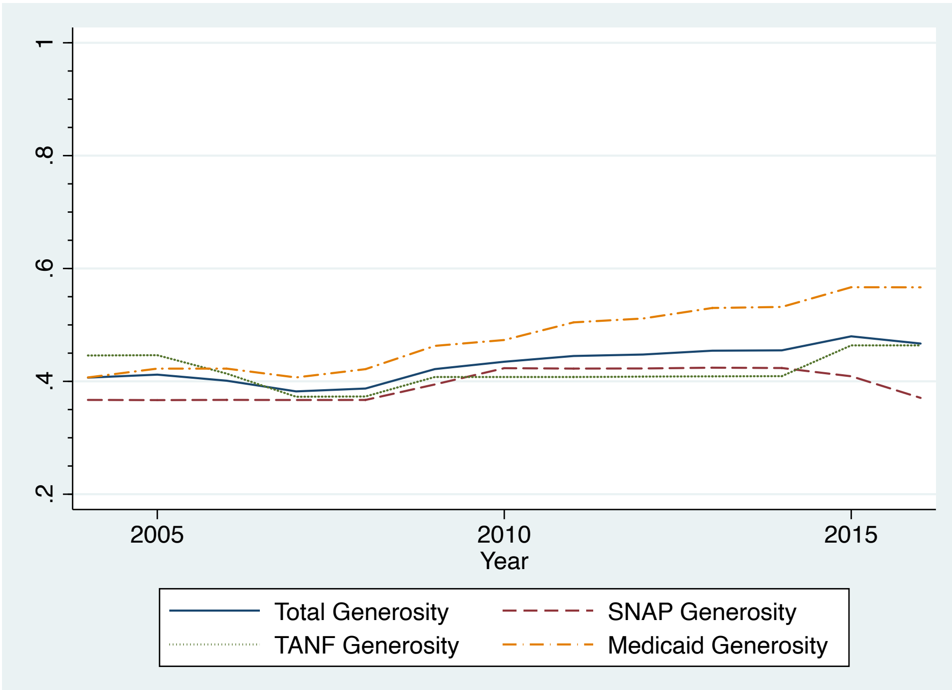
All graphs are shown on the same scale to aid in comparison across states.

Figure A.2.1 Alabama Generosity 2004–2016



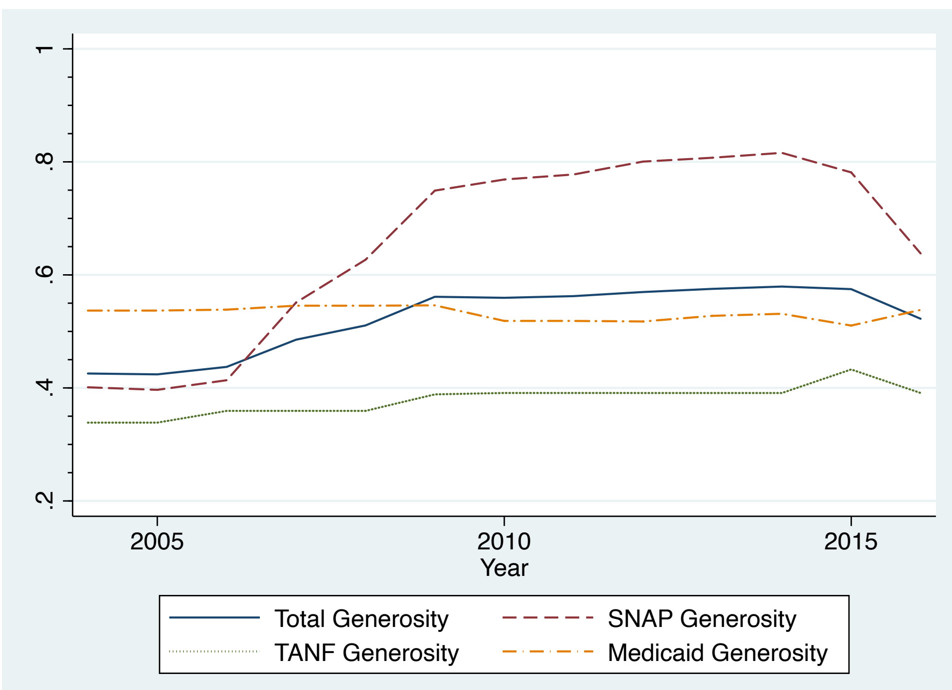
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.2 Alaska Generosity 2004–2016



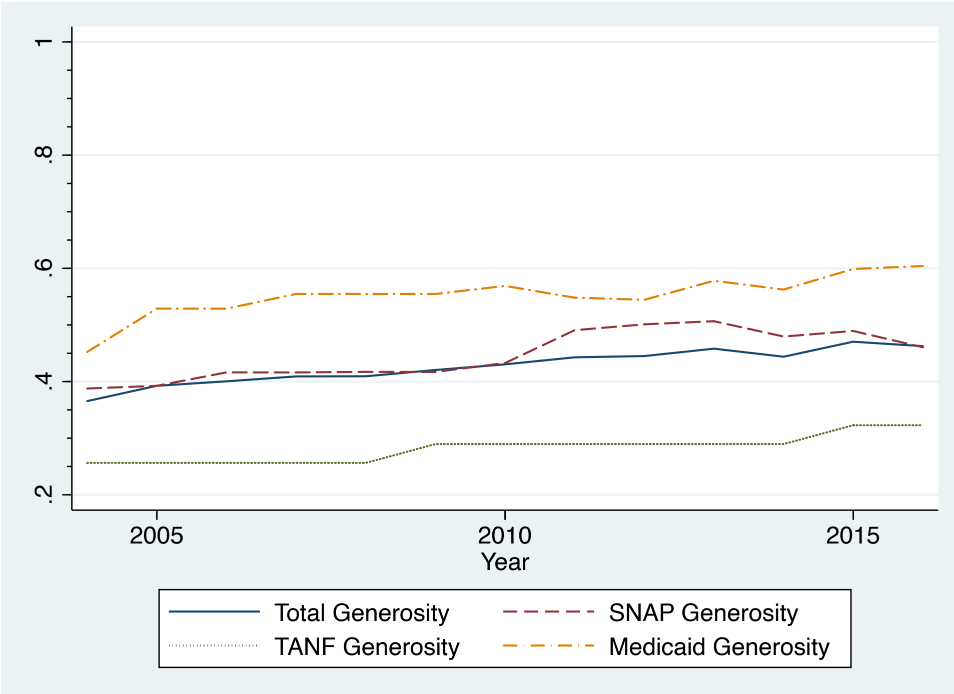
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.3 Arizona Generosity 2004–2016



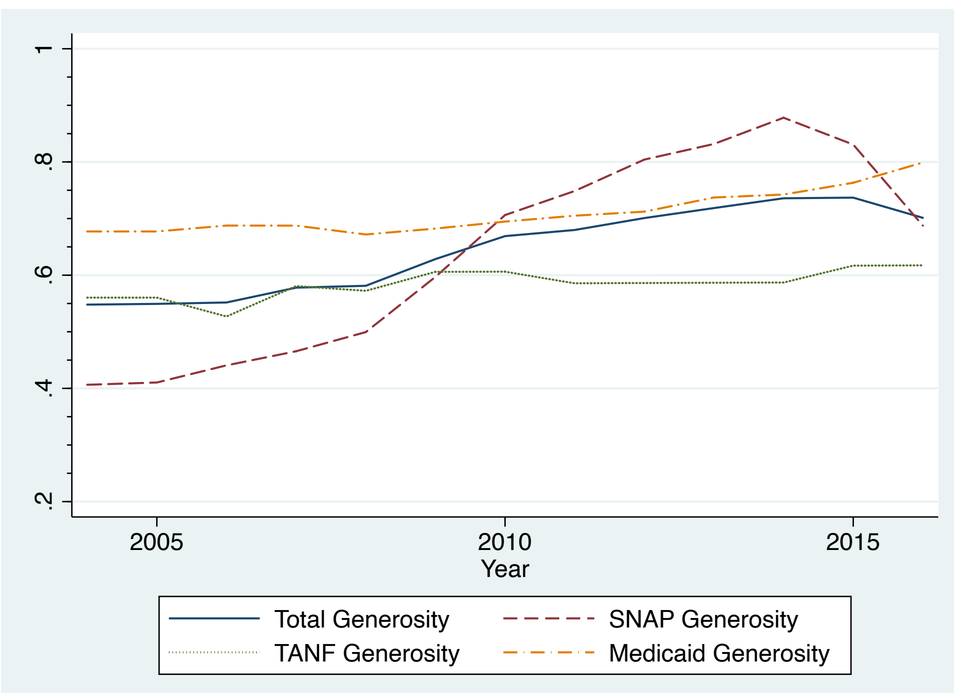
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.4 Arkansas Generosity 2004–2016



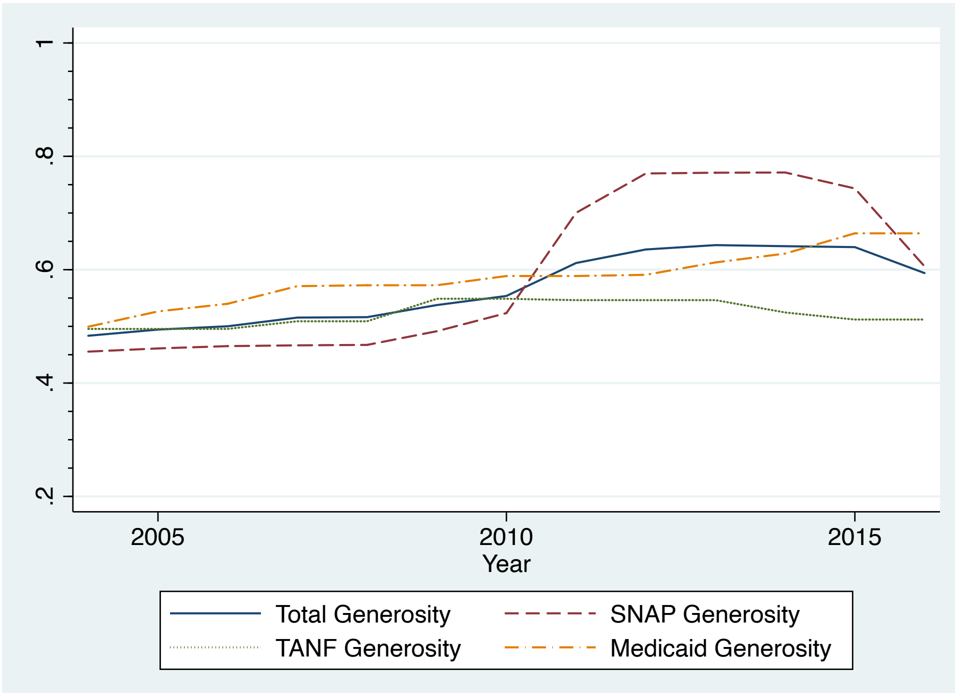
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.5 California Generosity 2004–2016



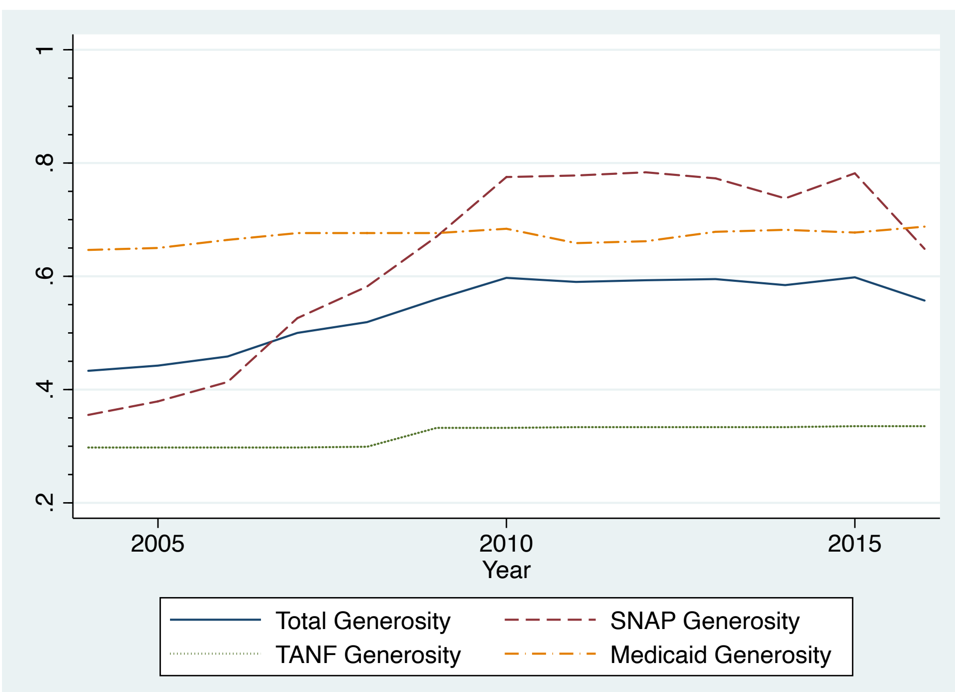
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.6 Colorado Generosity 2004–2016



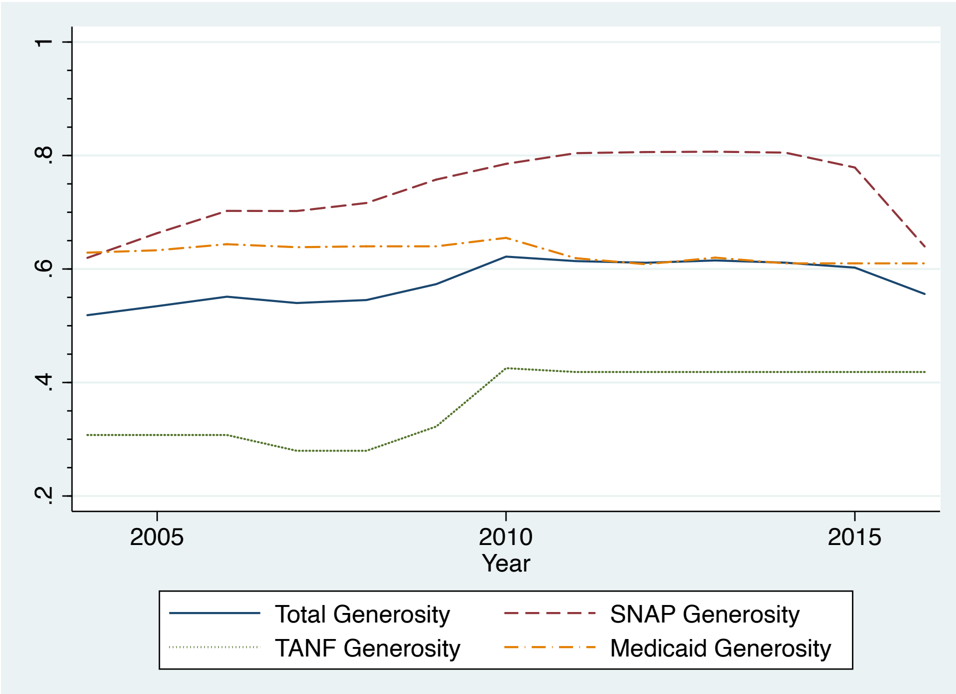
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.7 Connecticut Generosity 2004–2016



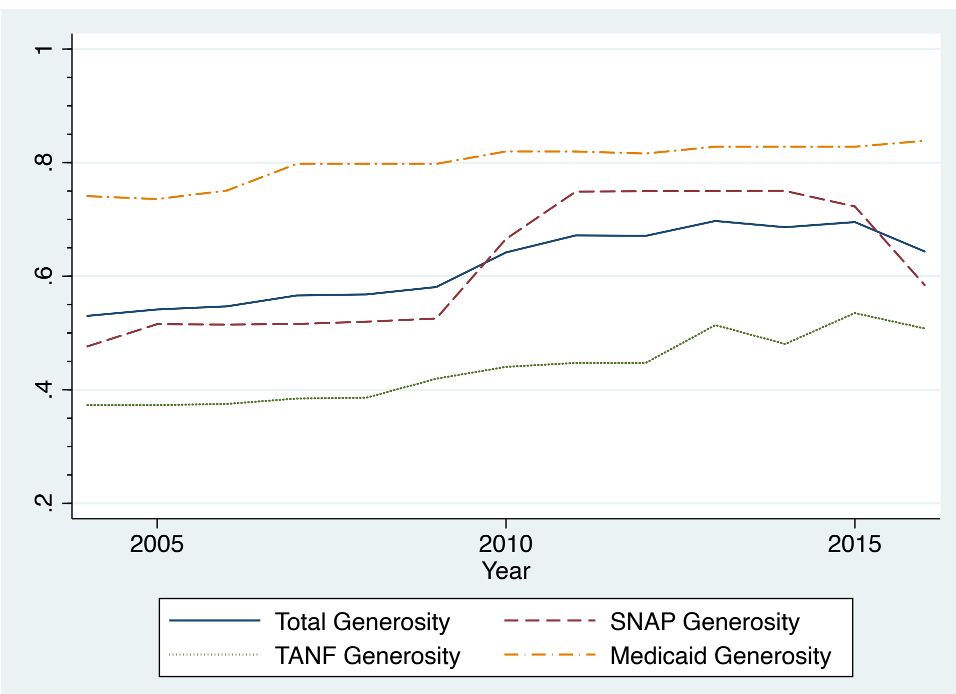
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.8 Delaware Generosity 2004–2016



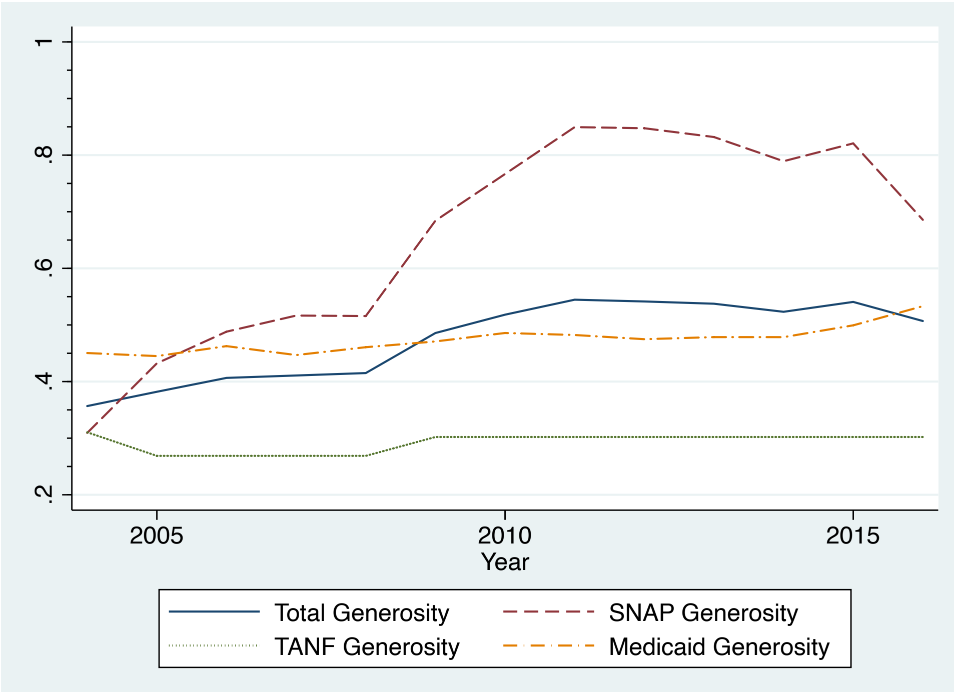
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.9 District of Columbia Generosity 2004–2016



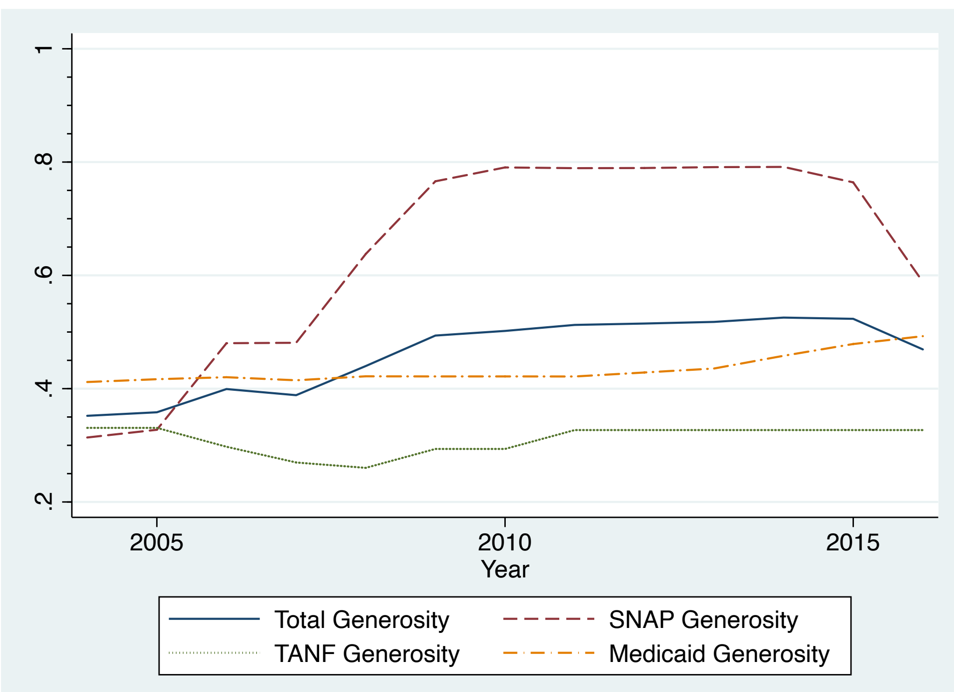
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.10 Florida Generosity 2004–2016



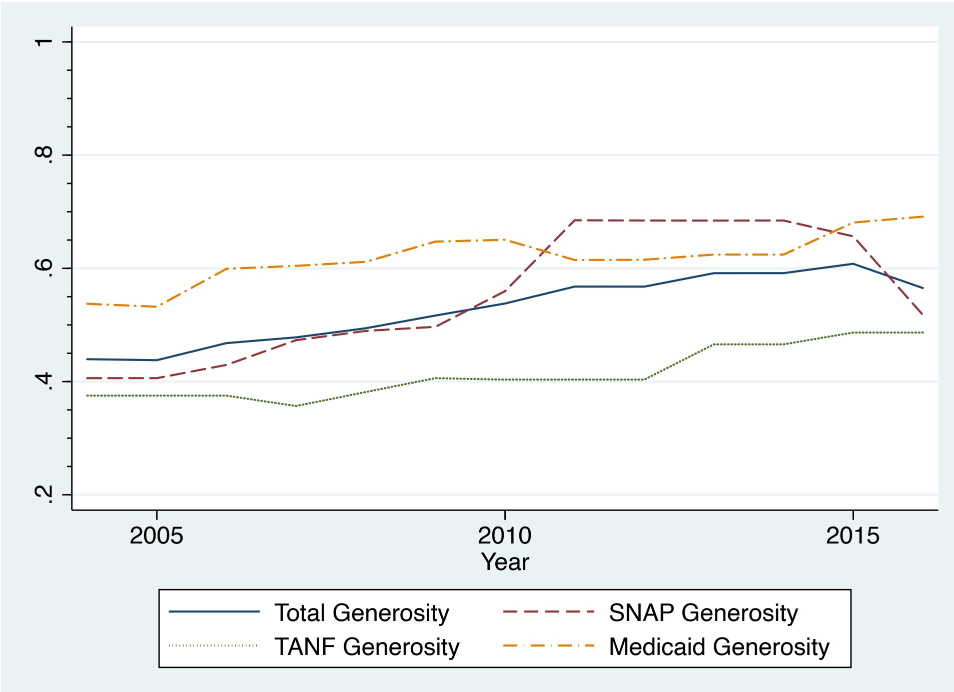
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.11 Georgia Generosity 2004–2016



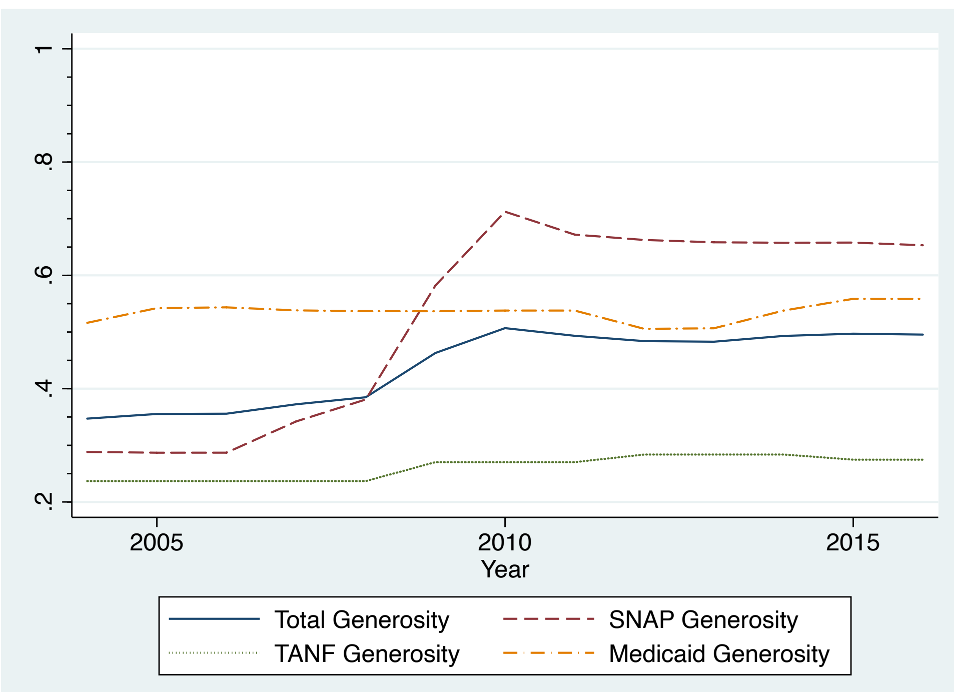
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.12 Hawaii Generosity 2004–2016



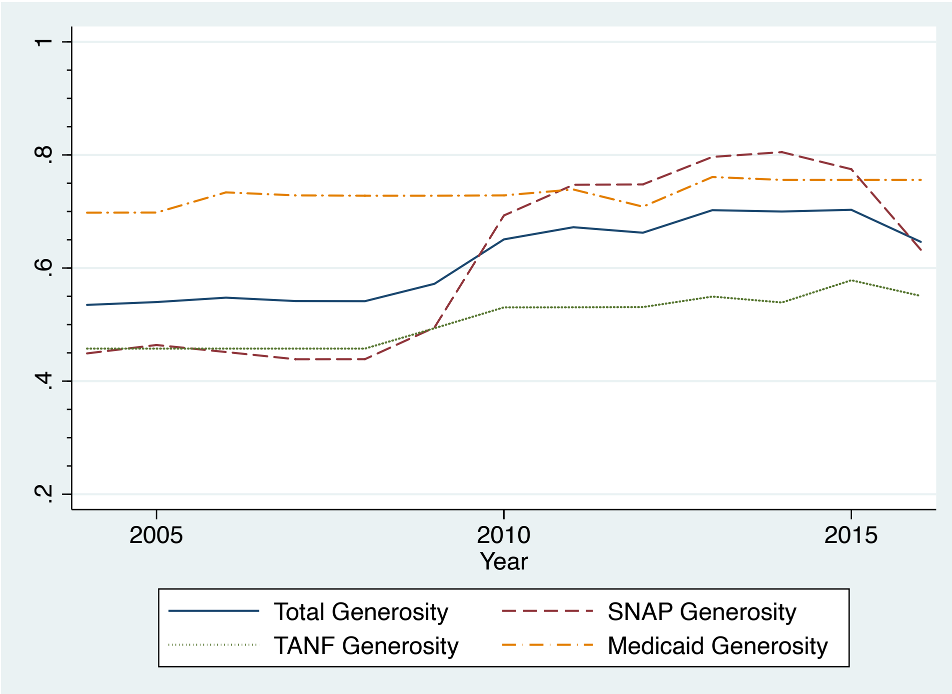
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.13 Idaho Generosity 2004–2016



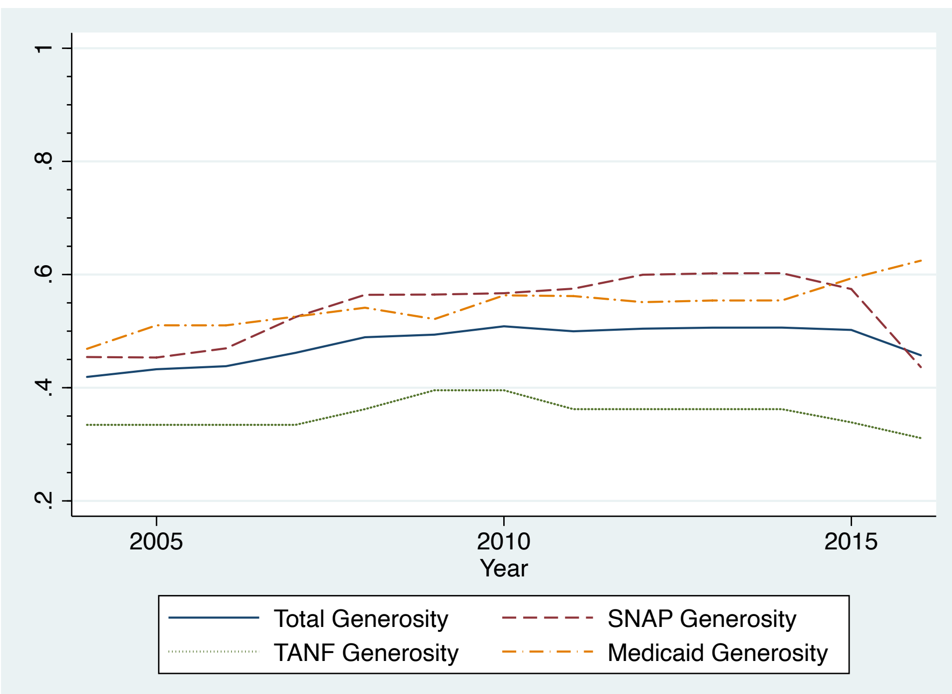
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.14 Illinois Generosity 2004–2016



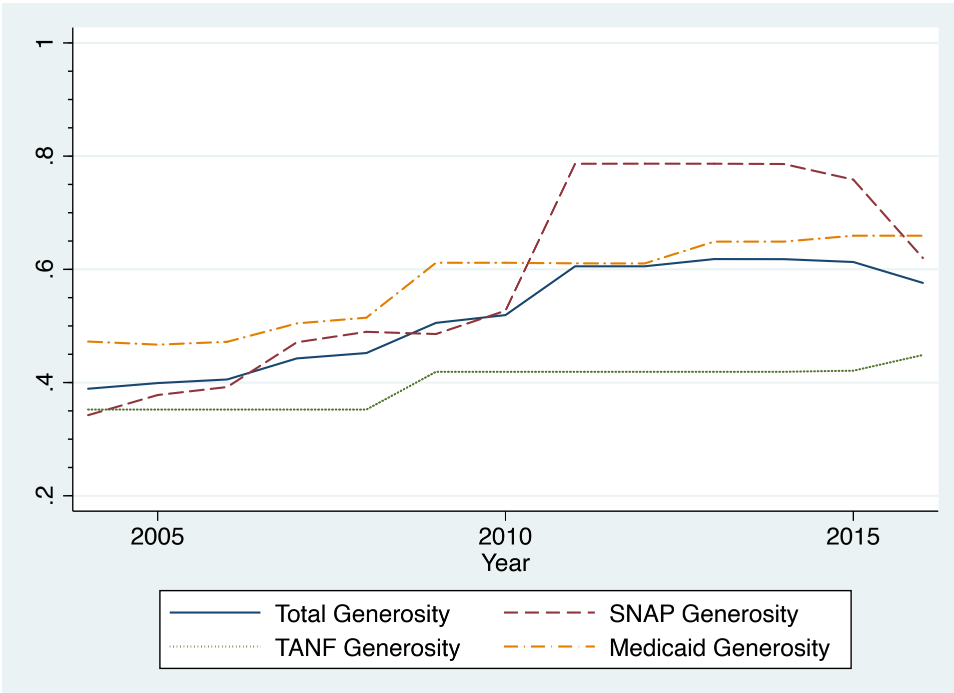
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.15 Indiana Generosity 2004–2016



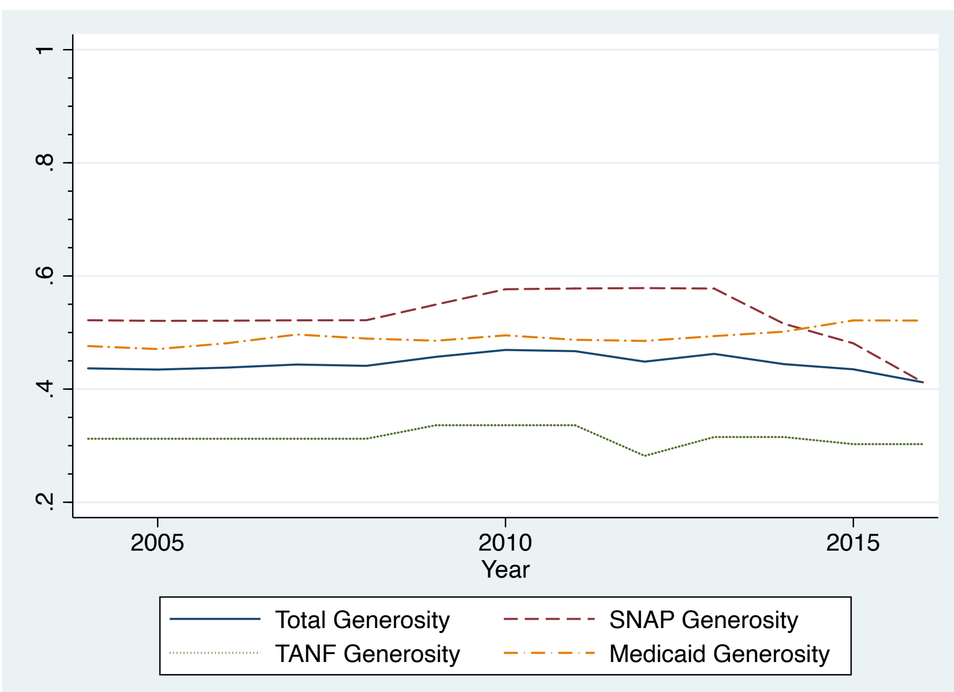
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.16 Iowa Generosity 2004–2016



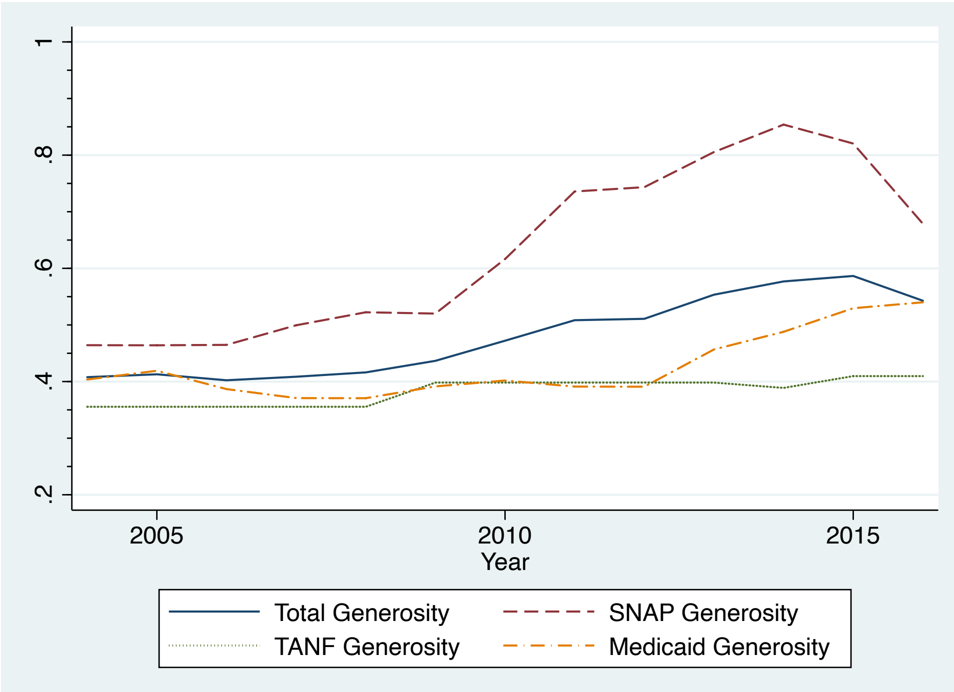
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.17 Kansas Generosity 2004–2016



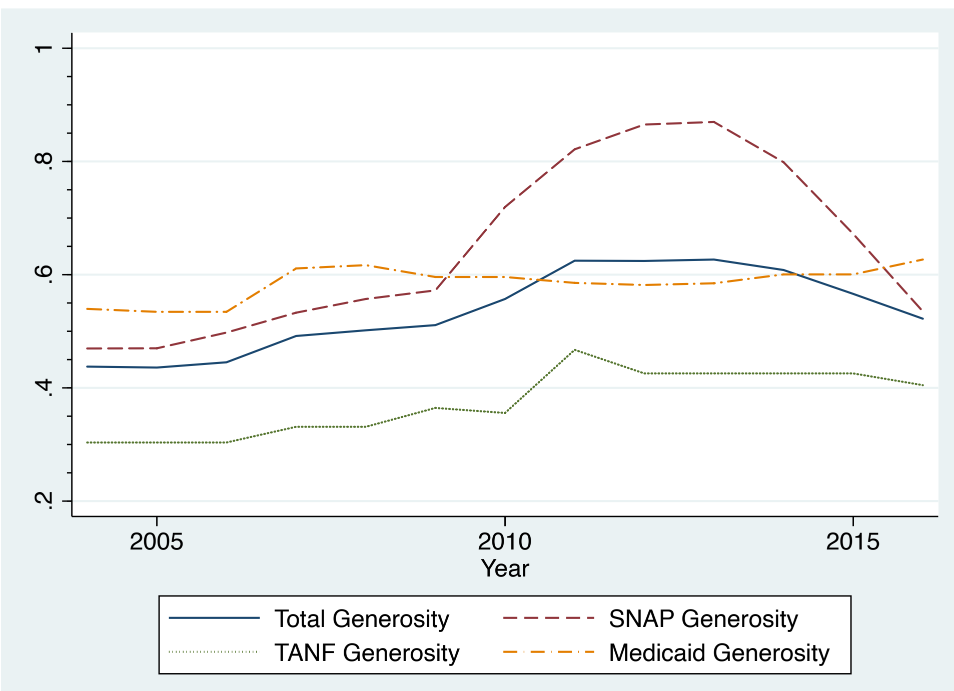
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.18 Kentucky Generosity 2004–2016



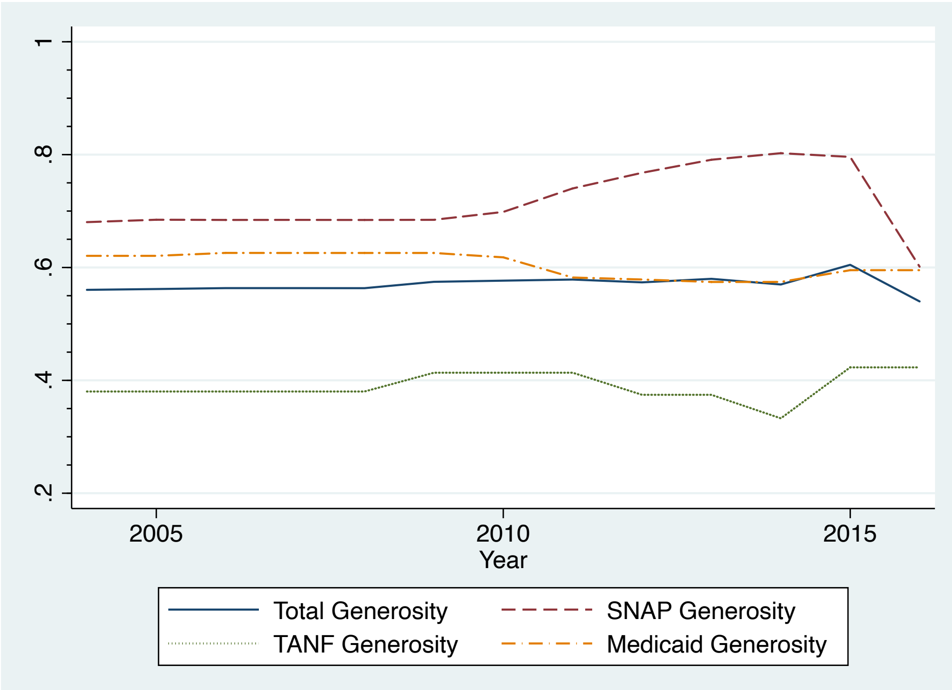
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.19 Louisiana Generosity 2004–2016



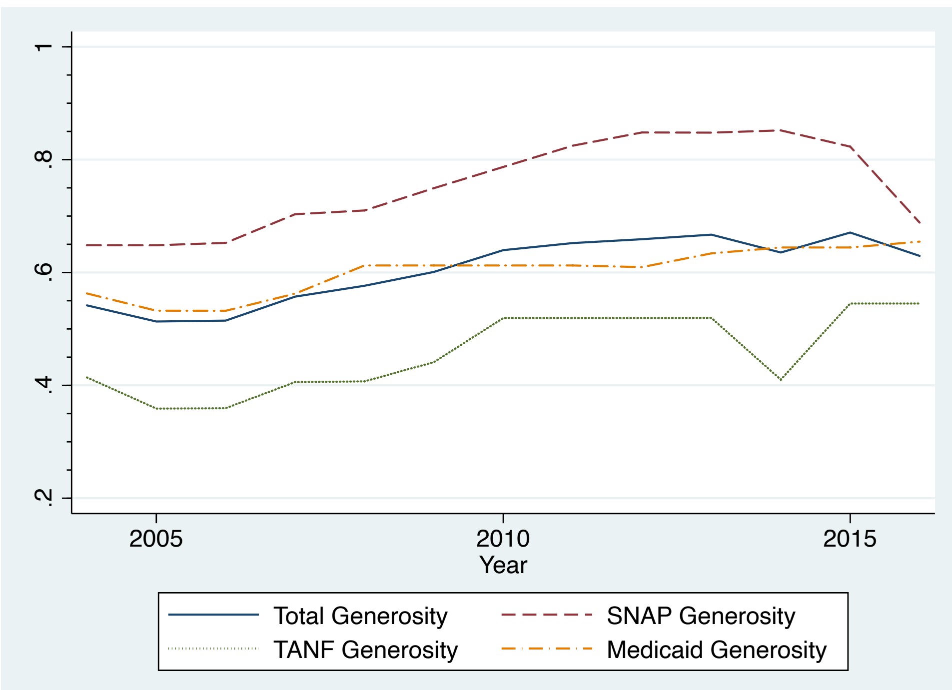
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.20 Maine Generosity 2004–2016



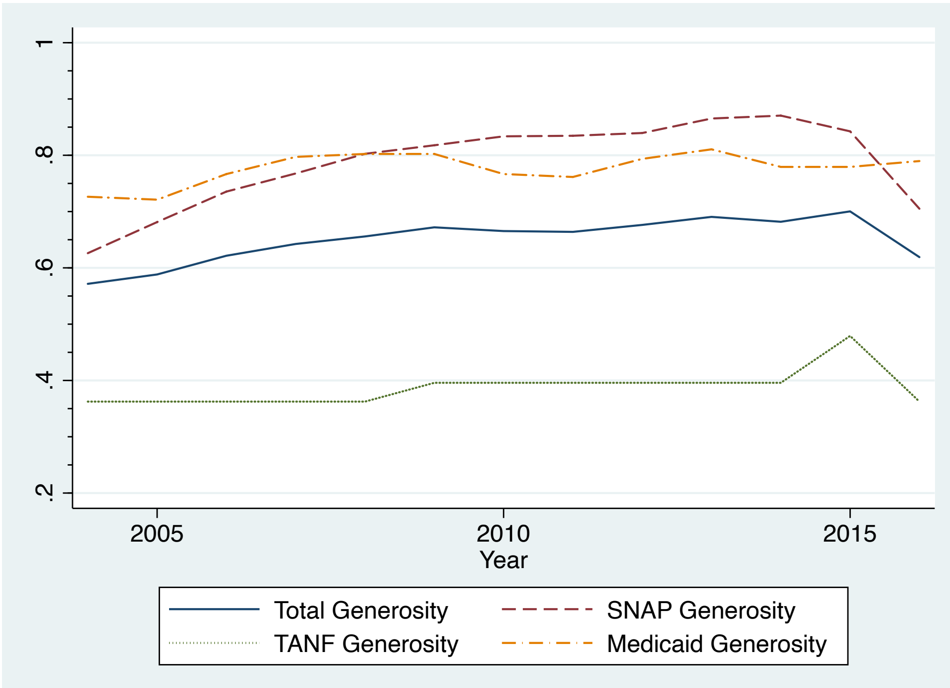
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.21 Maryland Generosity 2004–2016



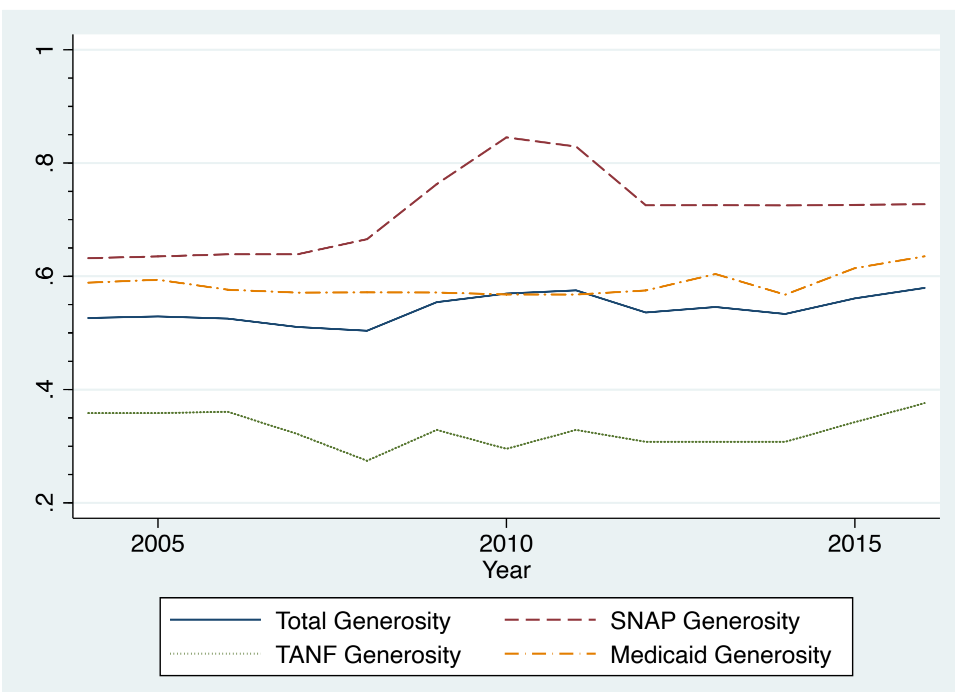
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.22 Massachusetts Generosity 2004–2016



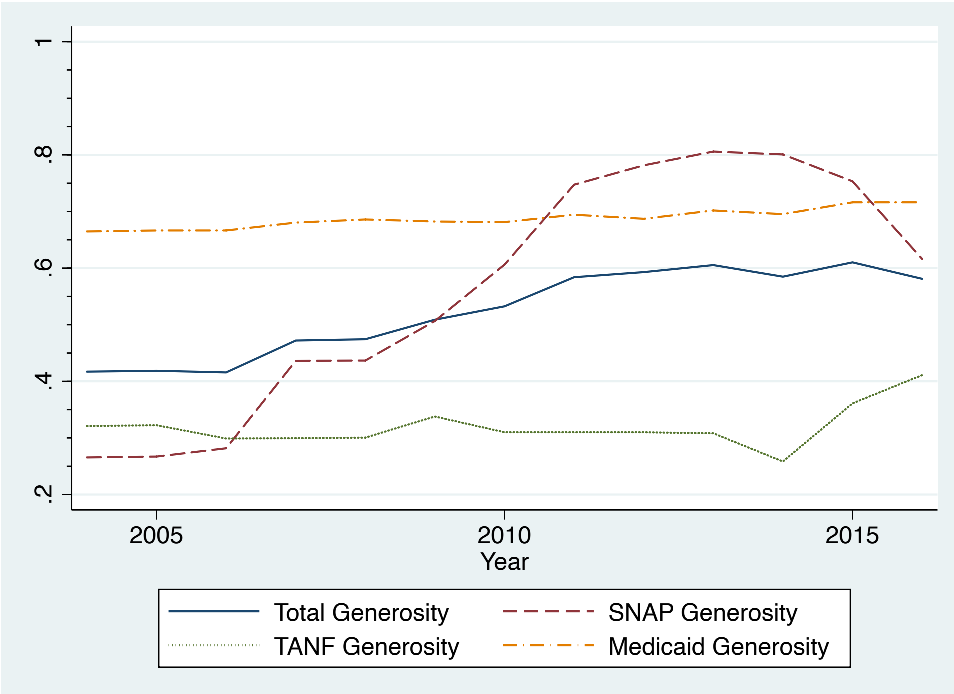
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.23 Michigan Generosity 2004–2016



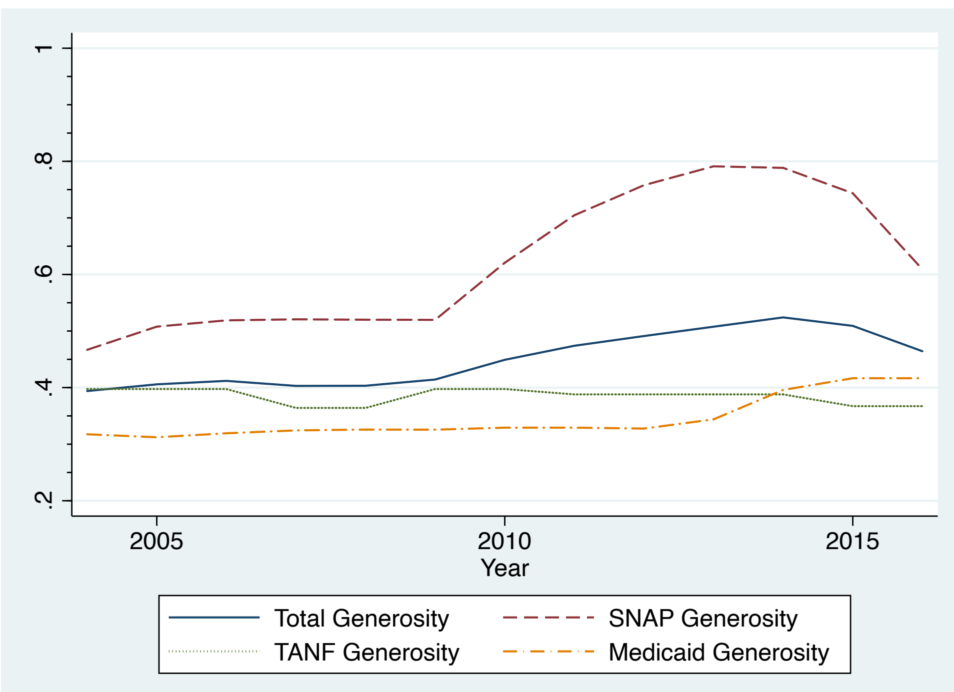
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.24 Minnesota Generosity 2004–2016



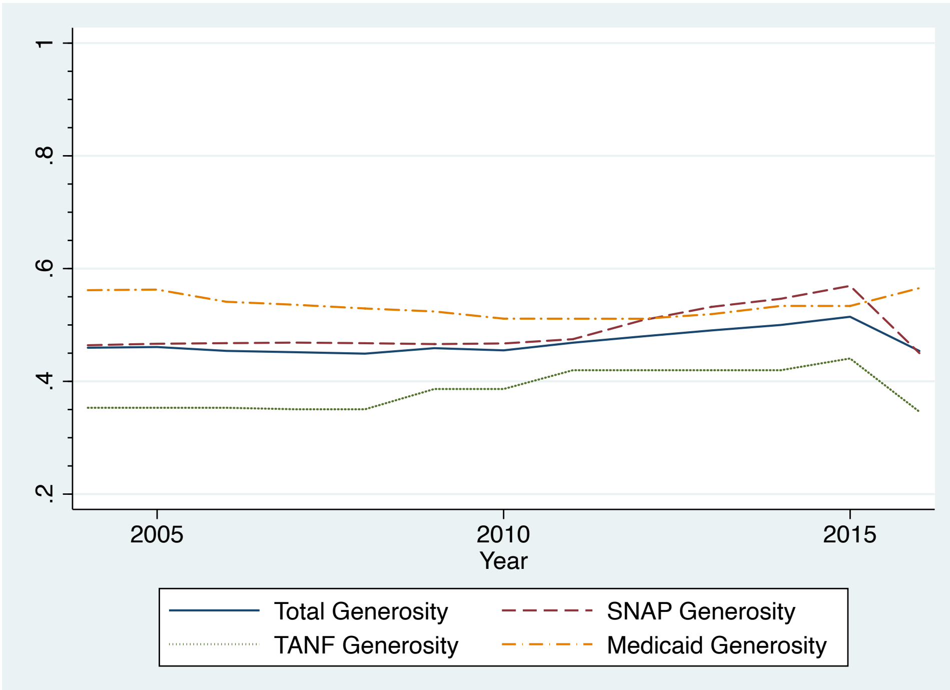
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.25 Mississippi Generosity 2004–2016



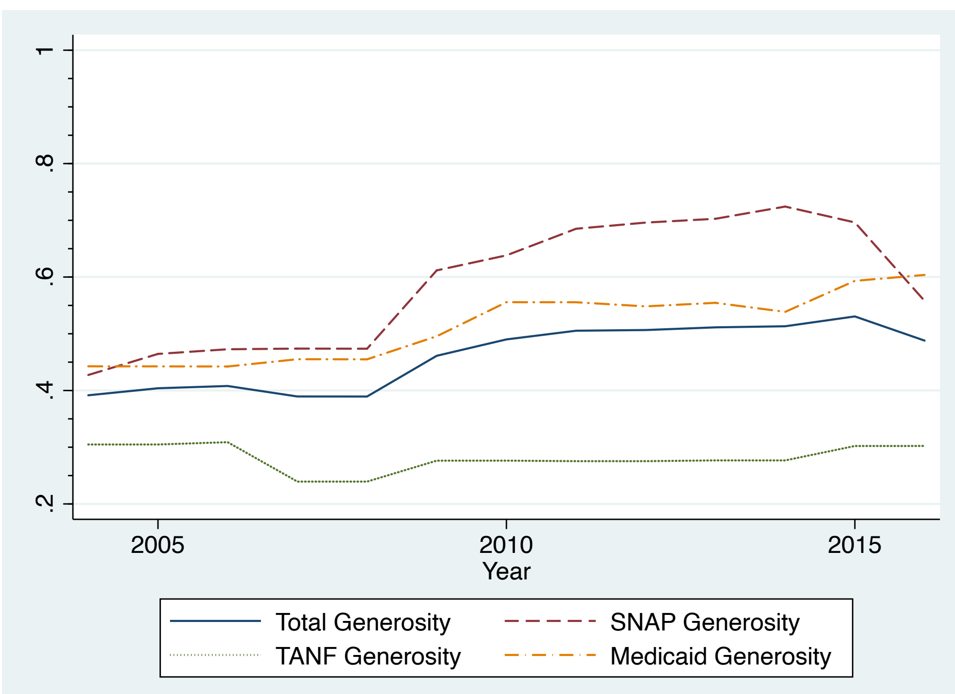
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.26 Missouri Generosity 2004–2016



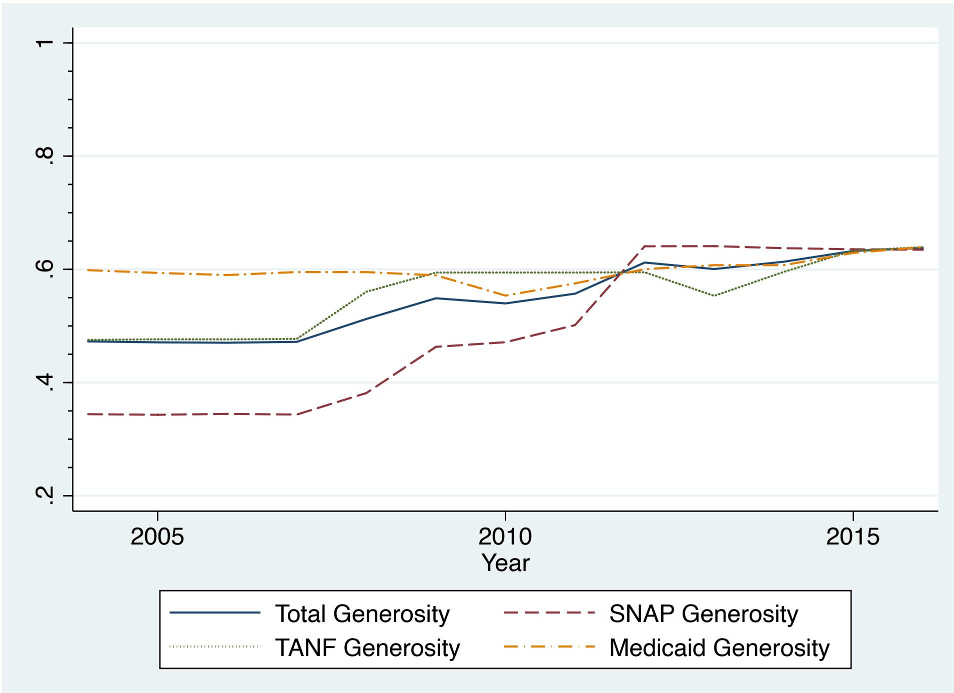
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.27 Montana Generosity 2004–2016



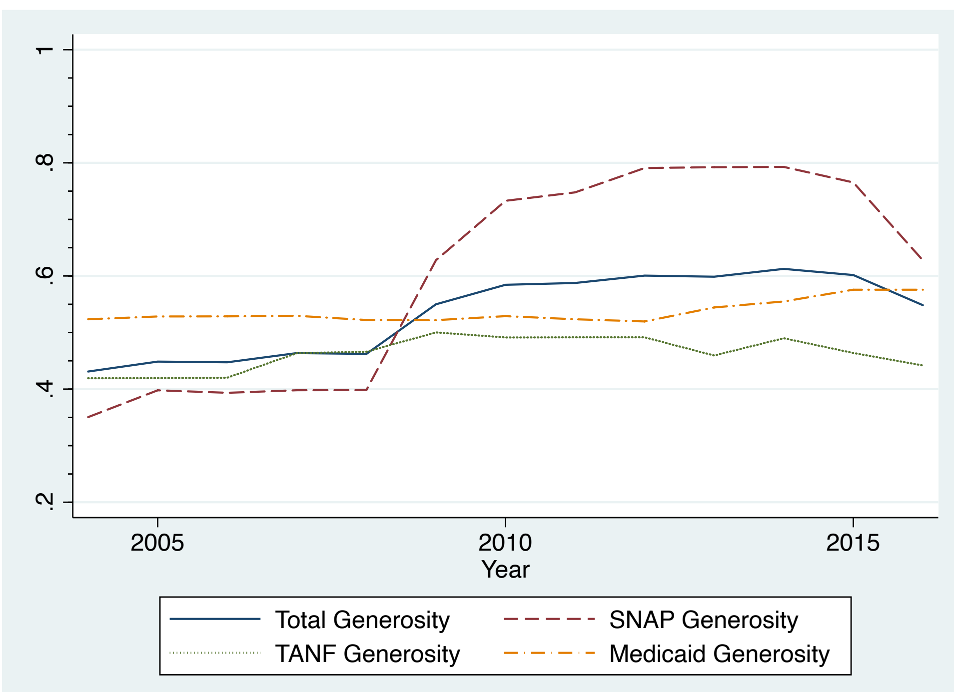
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.28 Nebraska Generosity 2004–2016



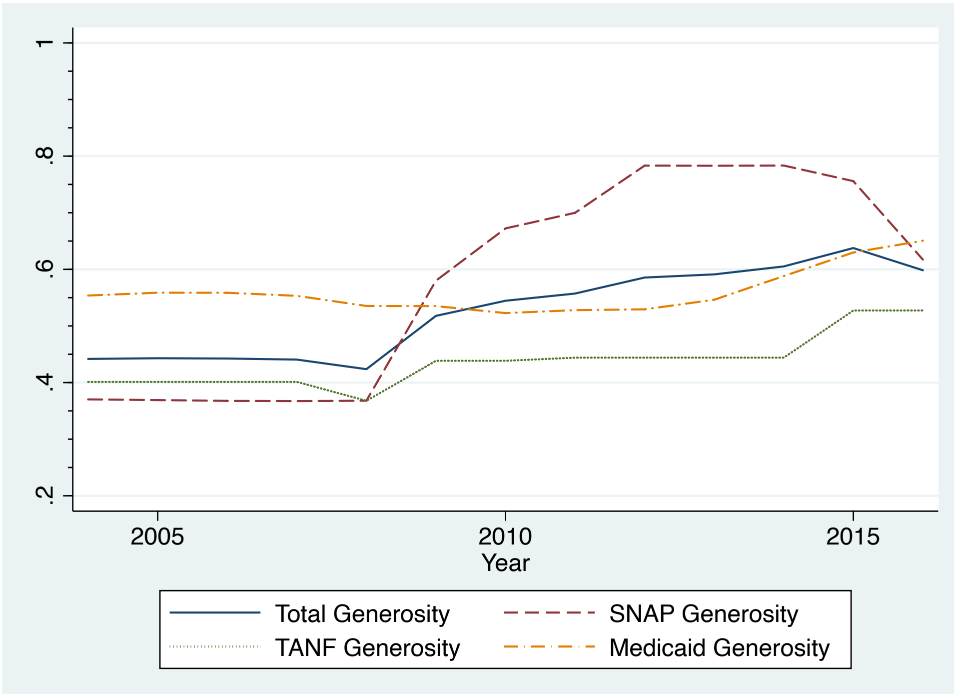
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.29 Nevada Generosity 2004–2016



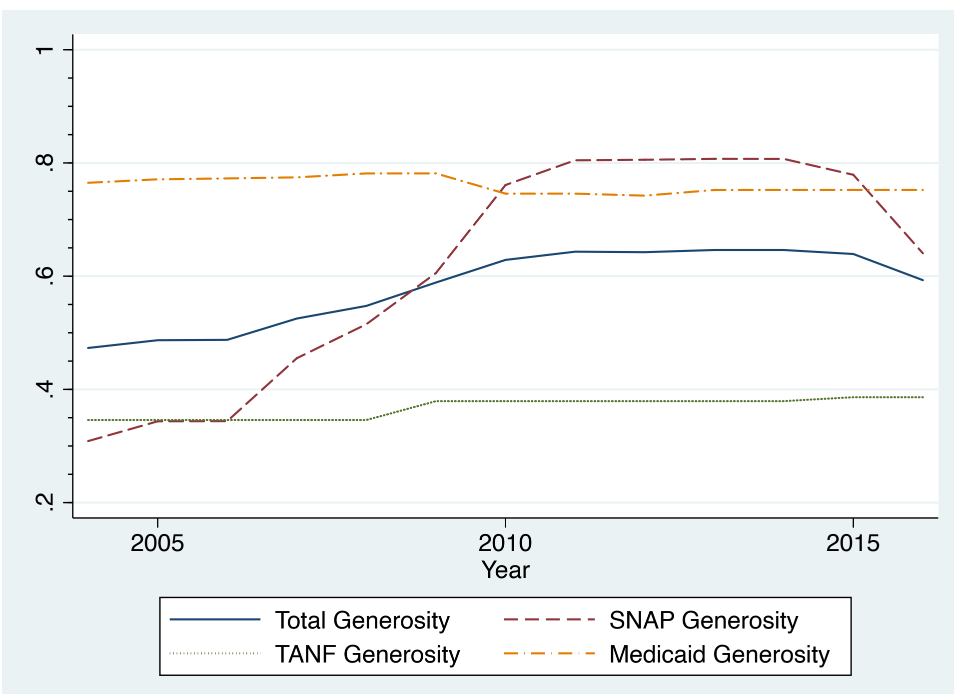
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.30 New Hampshire Generosity 2004–2016



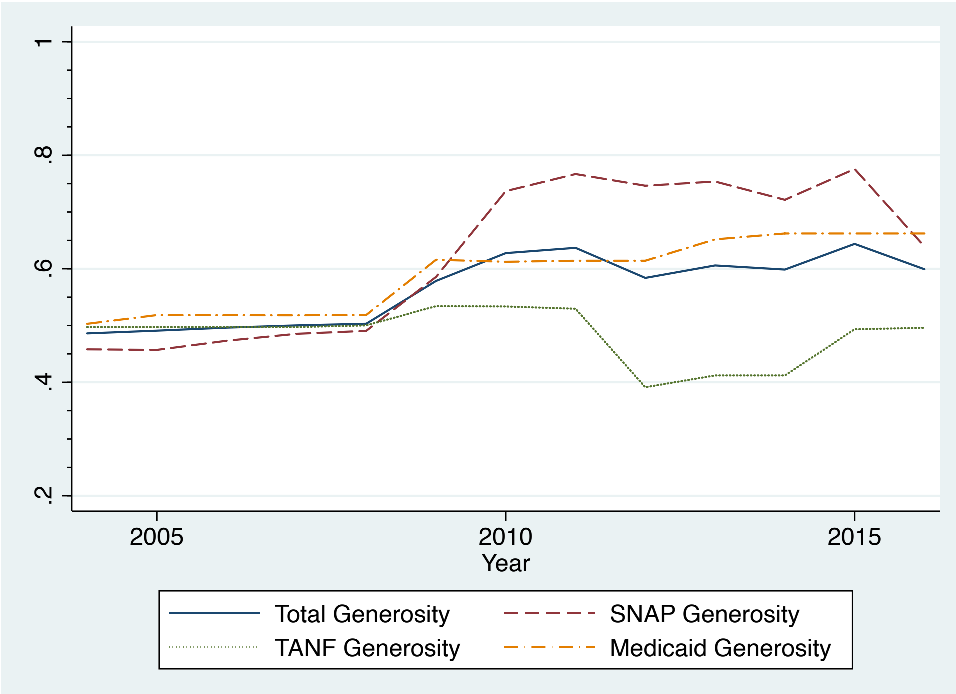
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.31 New Jersey Generosity 2004–2016



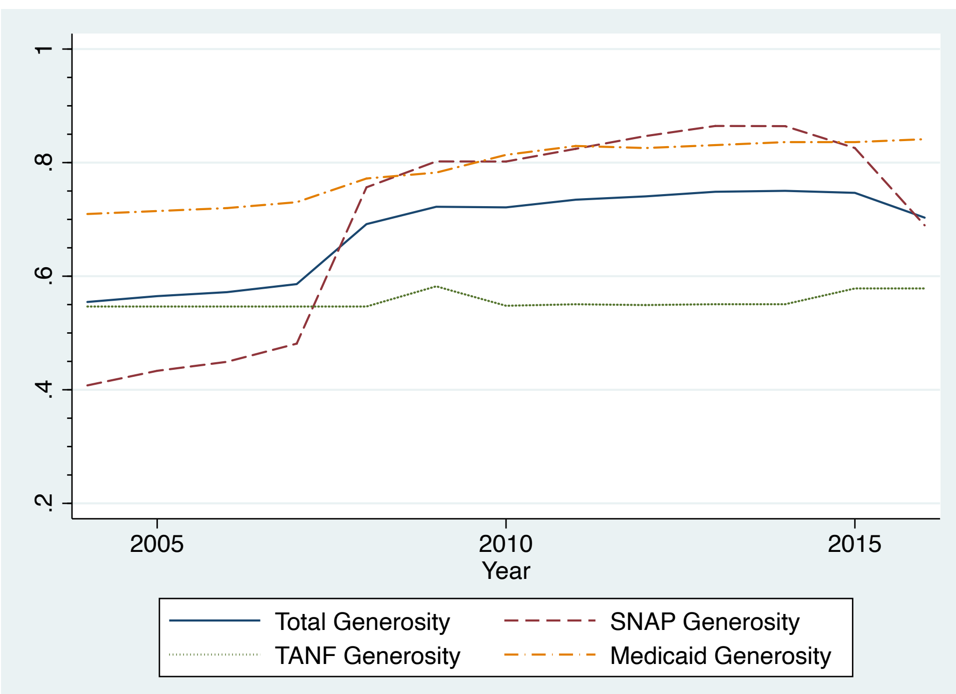
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.32 New Mexico Generosity 2004–2016



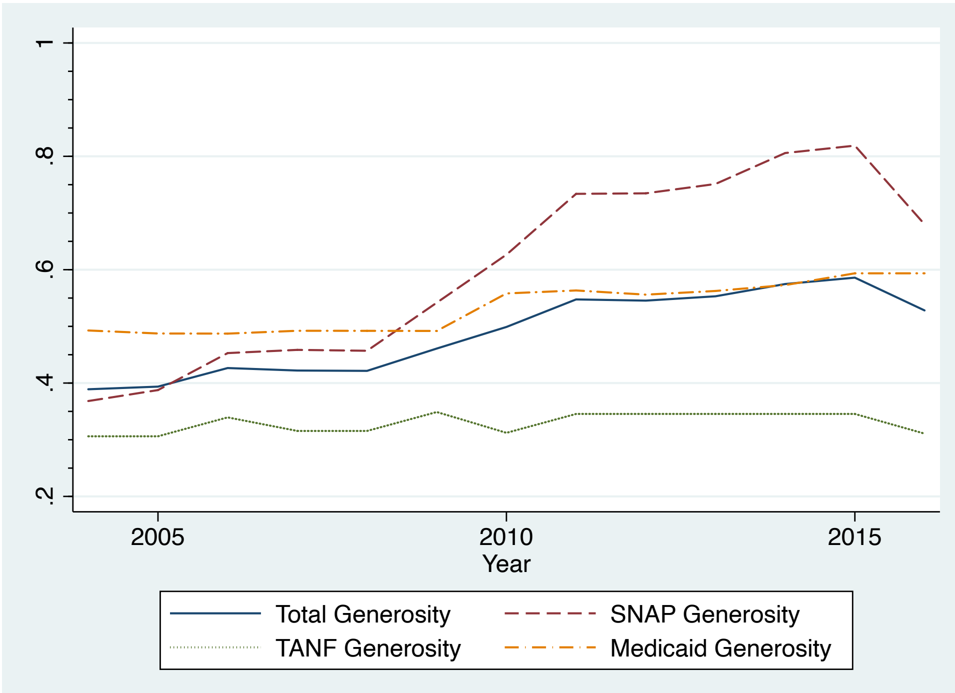
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.33 New York Generosity 2004–2016



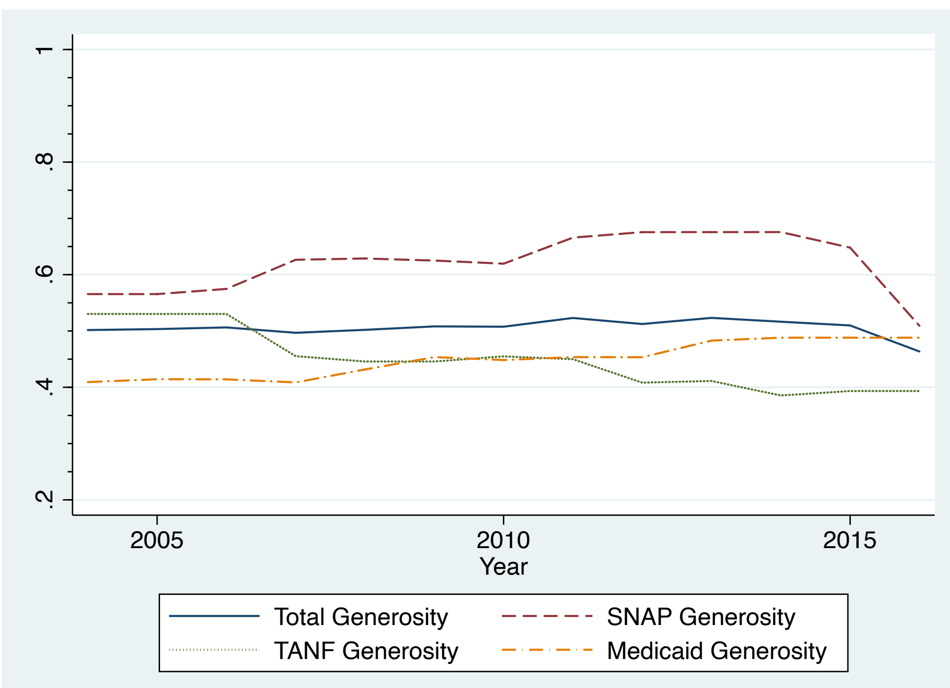
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.34 North Carolina Generosity 2004–2016



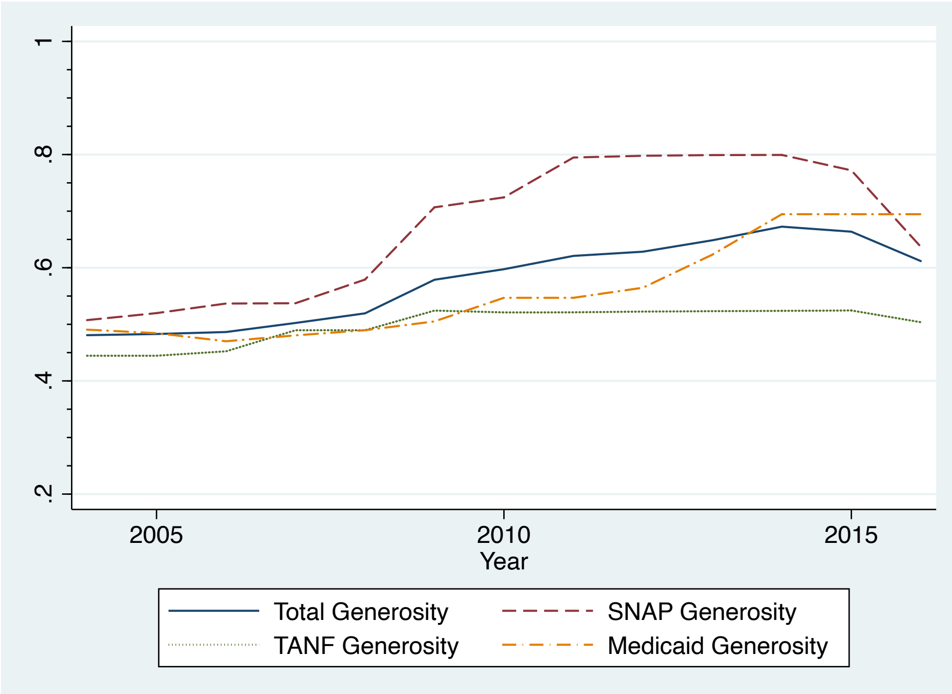
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.35 North Dakota Generosity 2004–2016



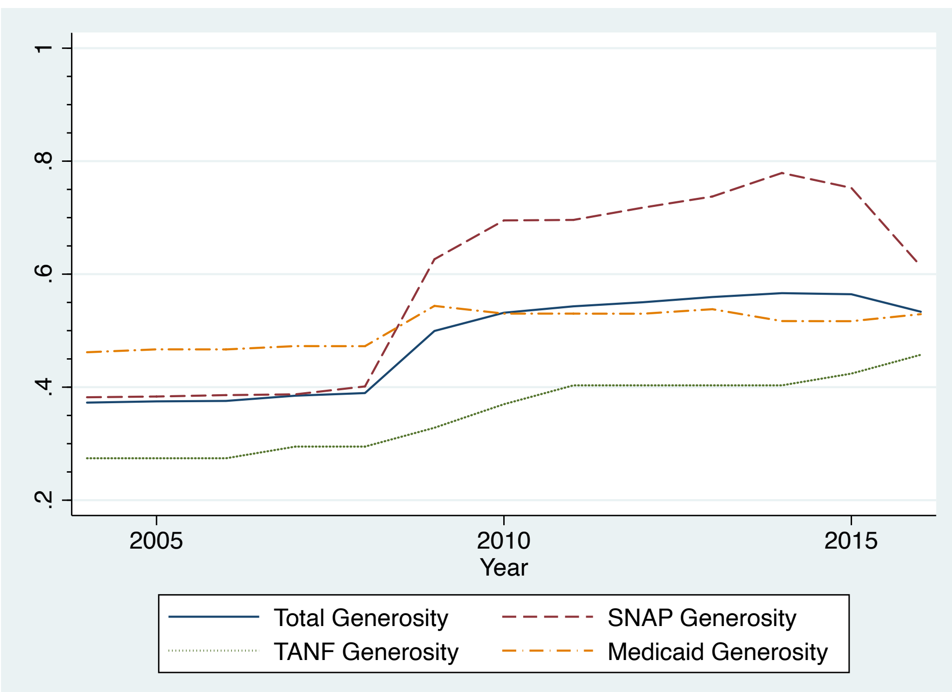
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.36 Ohio Generosity 2004–2016



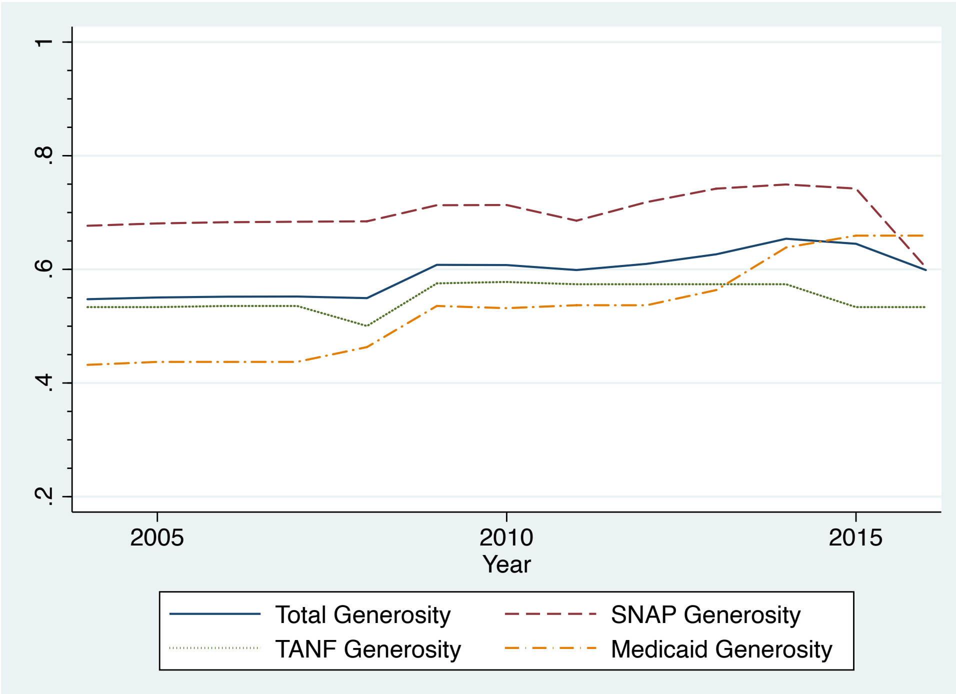
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.37 Oklahoma Generosity 2004–2016



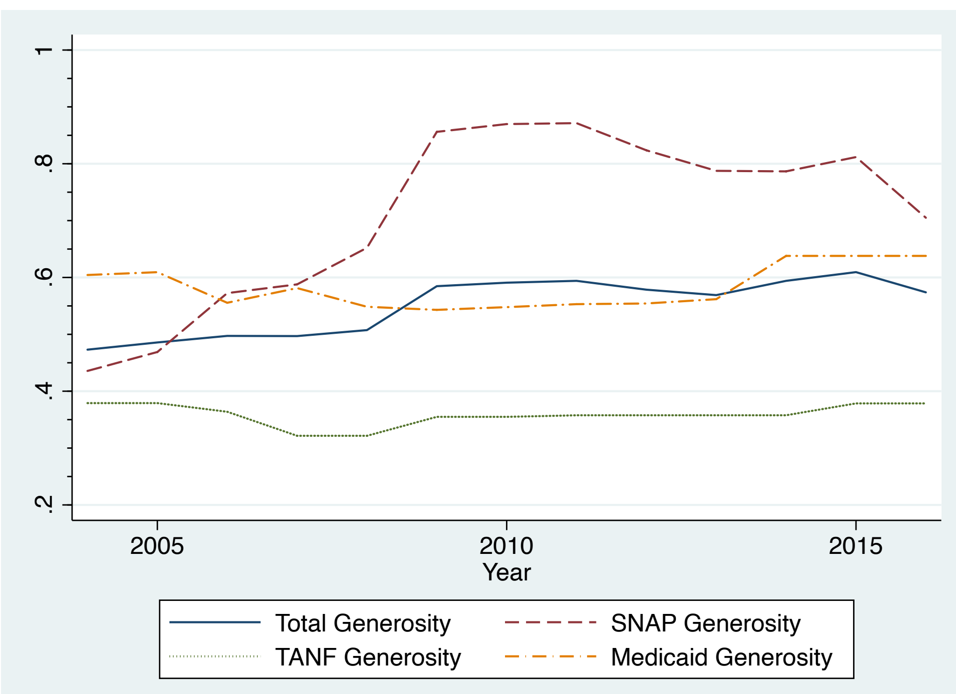
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.38 Oregon Generosity 2004–2016



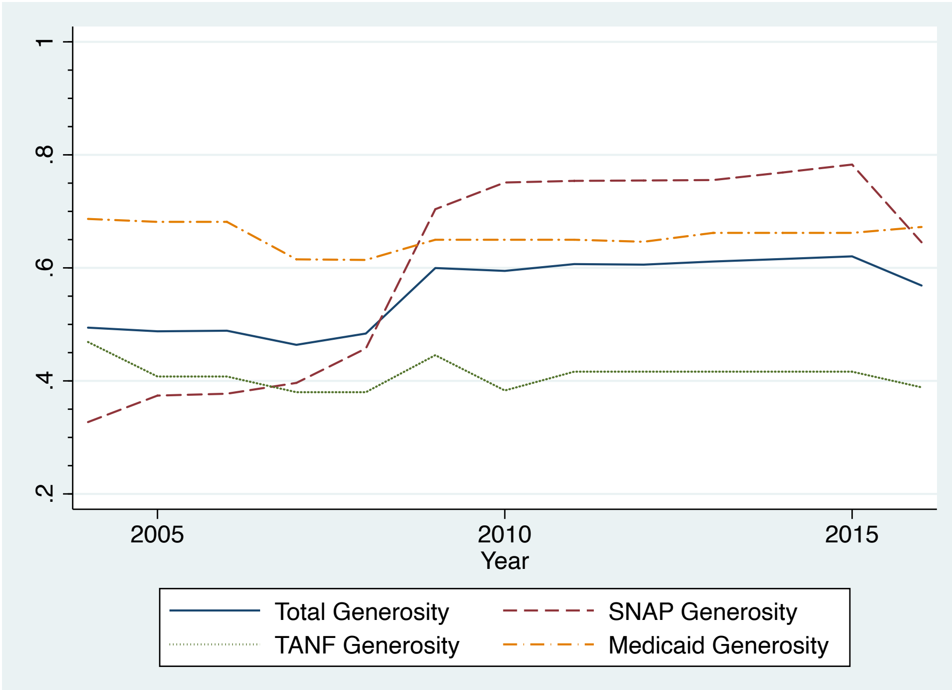
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.39 Pennsylvania Generosity 2004–2016



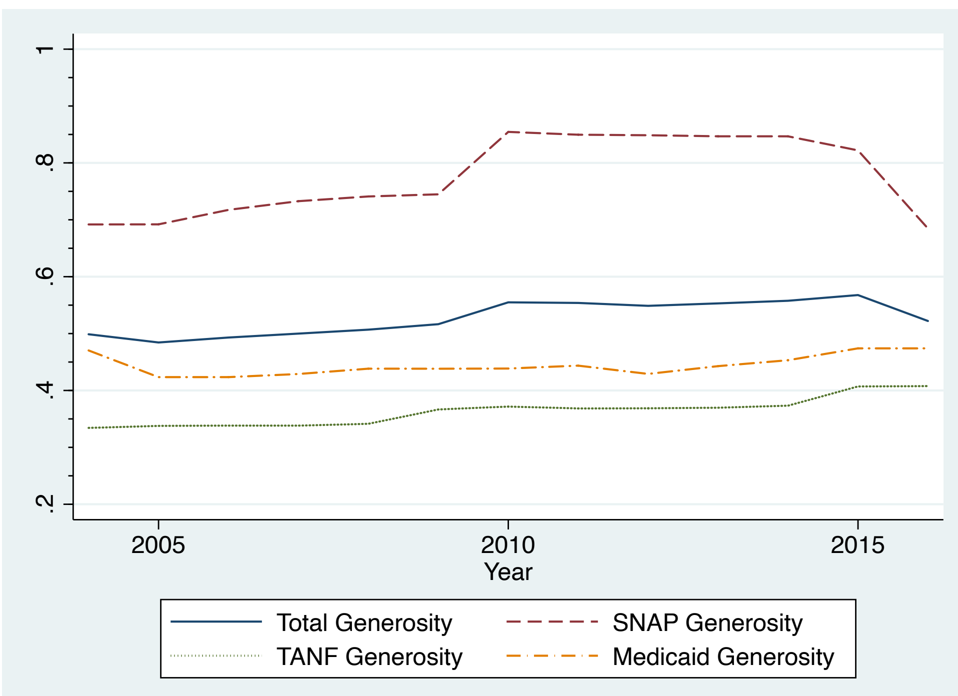
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.40 Rhode Island Generosity 2004–2016



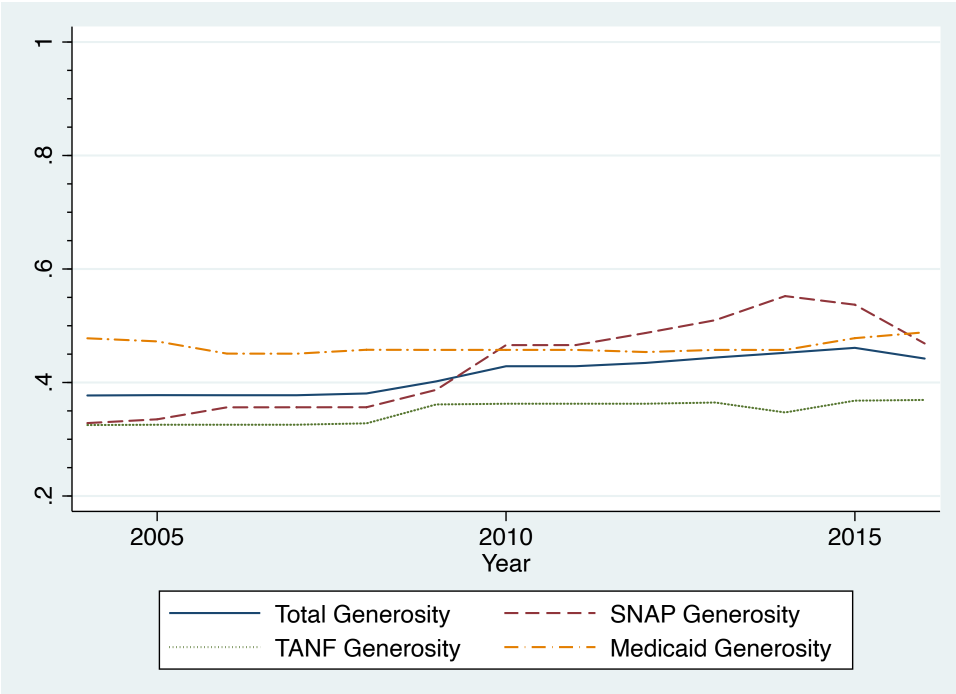
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.41 South Carolina Generosity 2004–2016



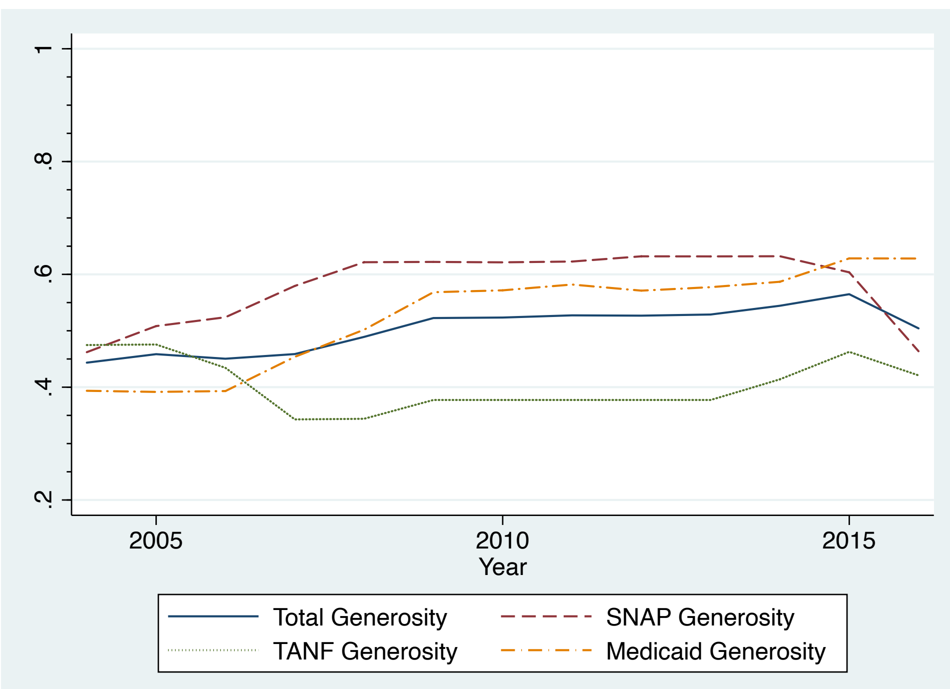
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.42 South Dakota Generosity 2004–2016



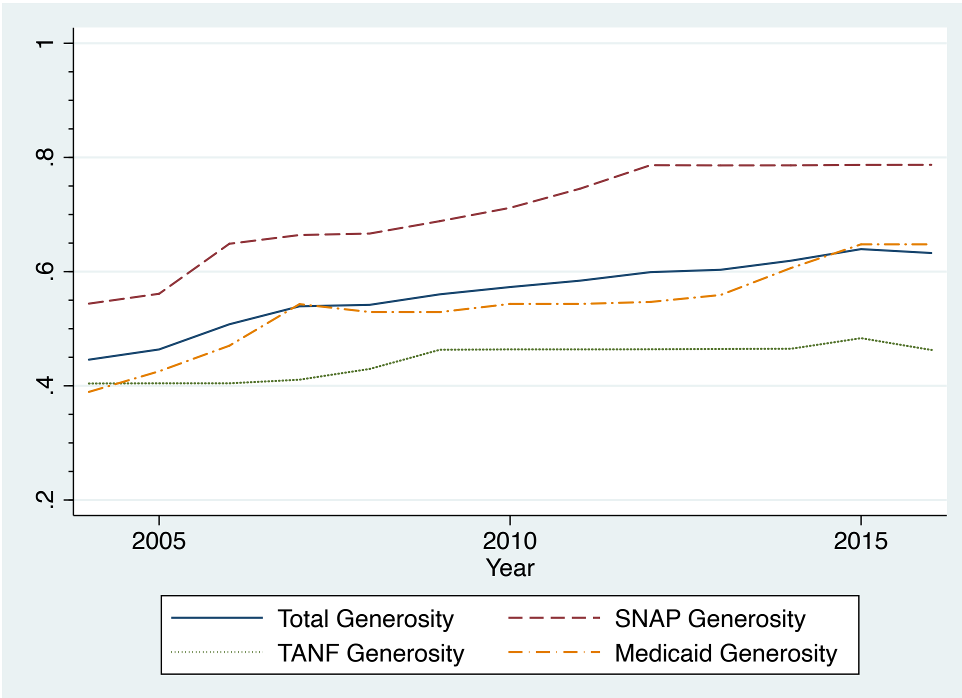
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.43 Tennessee Generosity 2004–2016



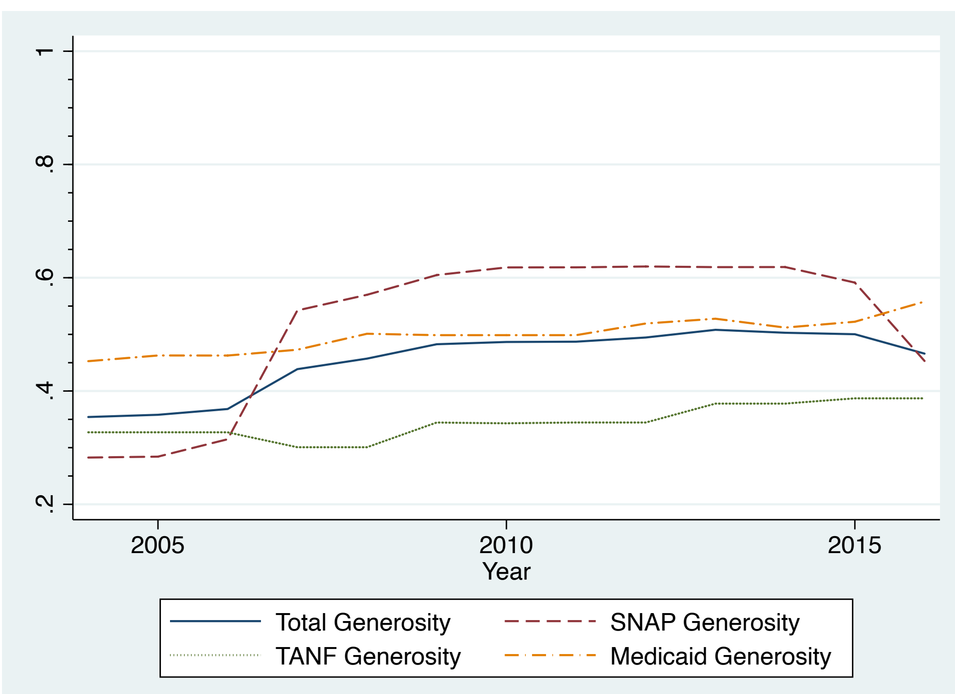
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.44 Texas Generosity 2004–2016



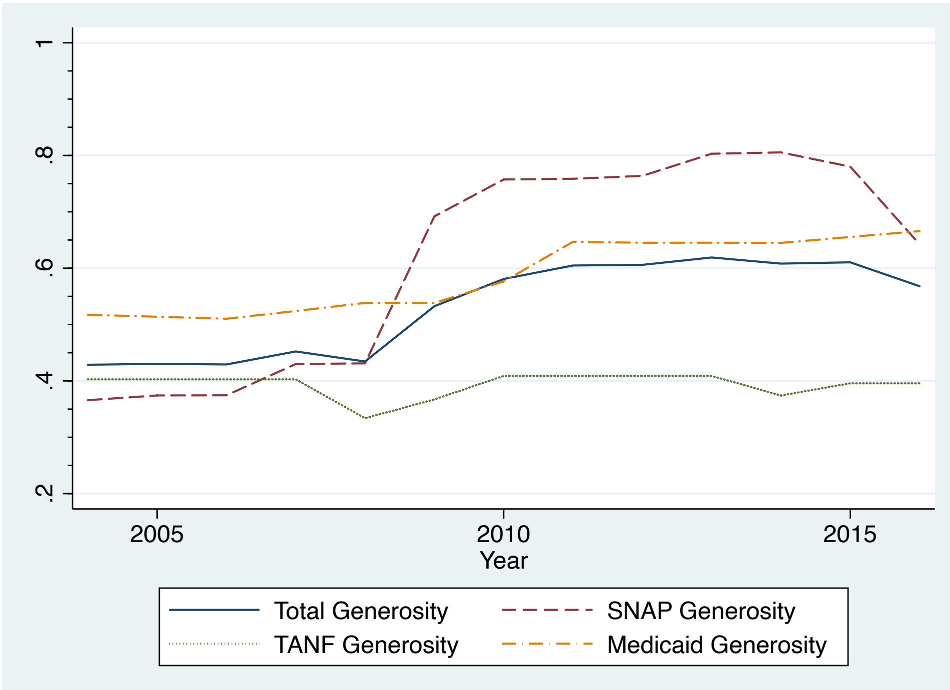
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.45 Utah Generosity 2004–2016



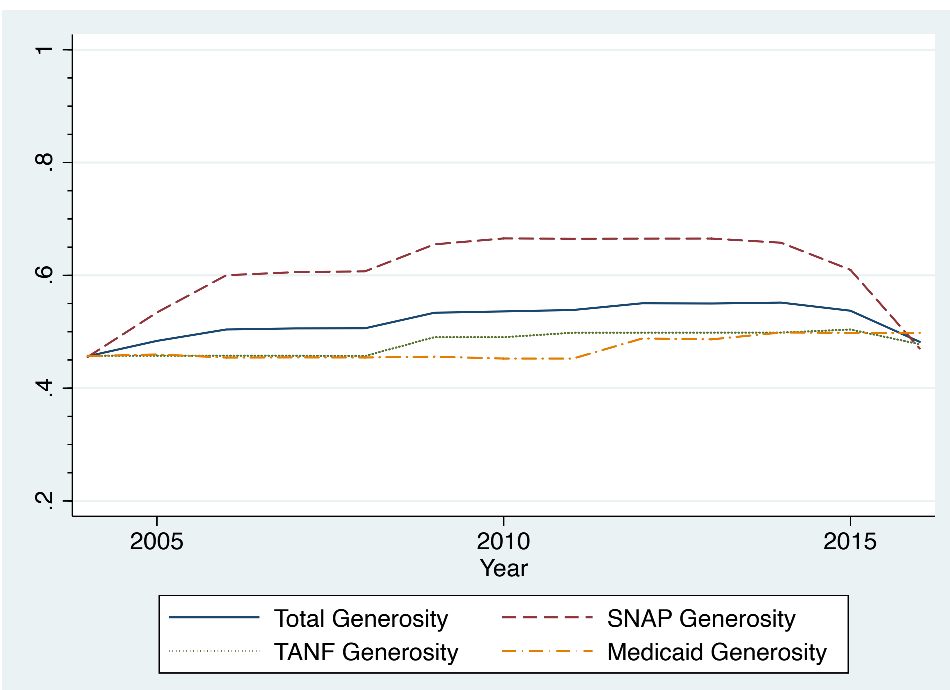
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.46 Vermont Generosity 2004–2016



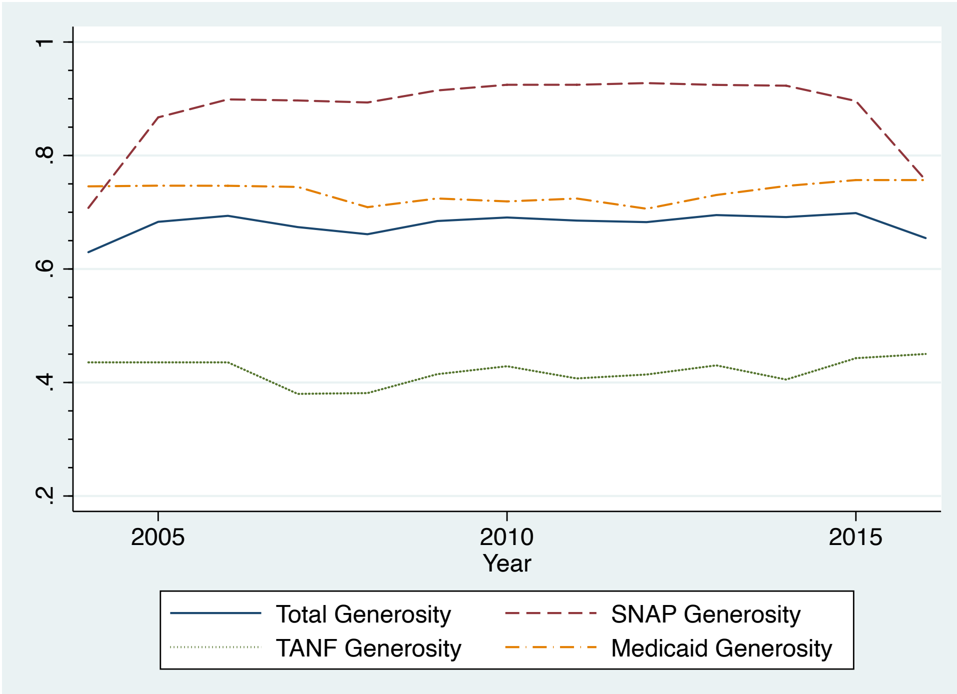
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.47 Virginia Generosity 2004–2016



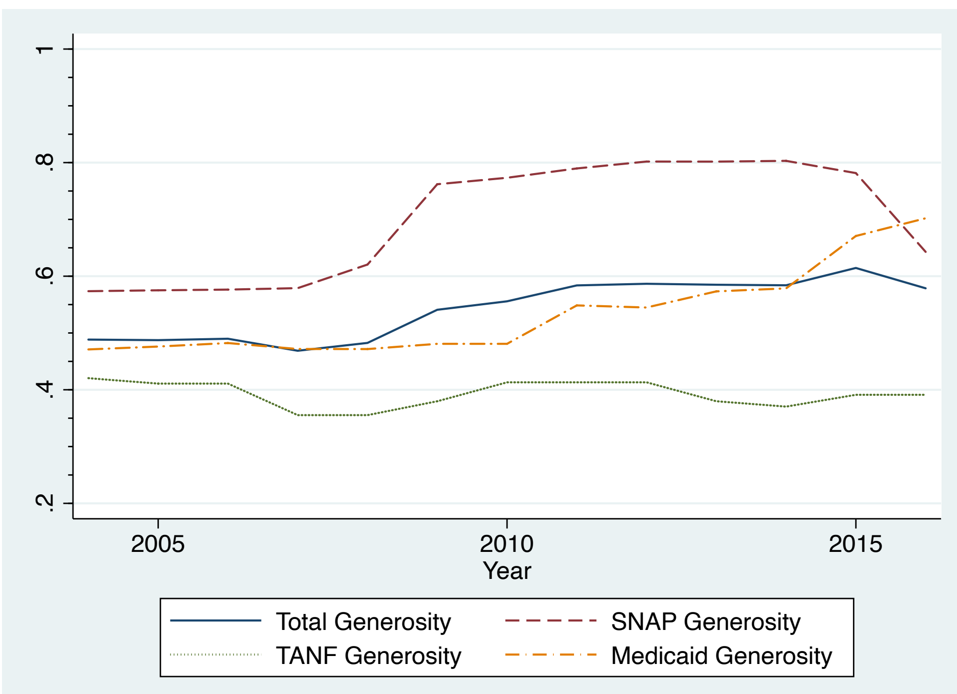
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.48 Washington Generosity 2004–2016



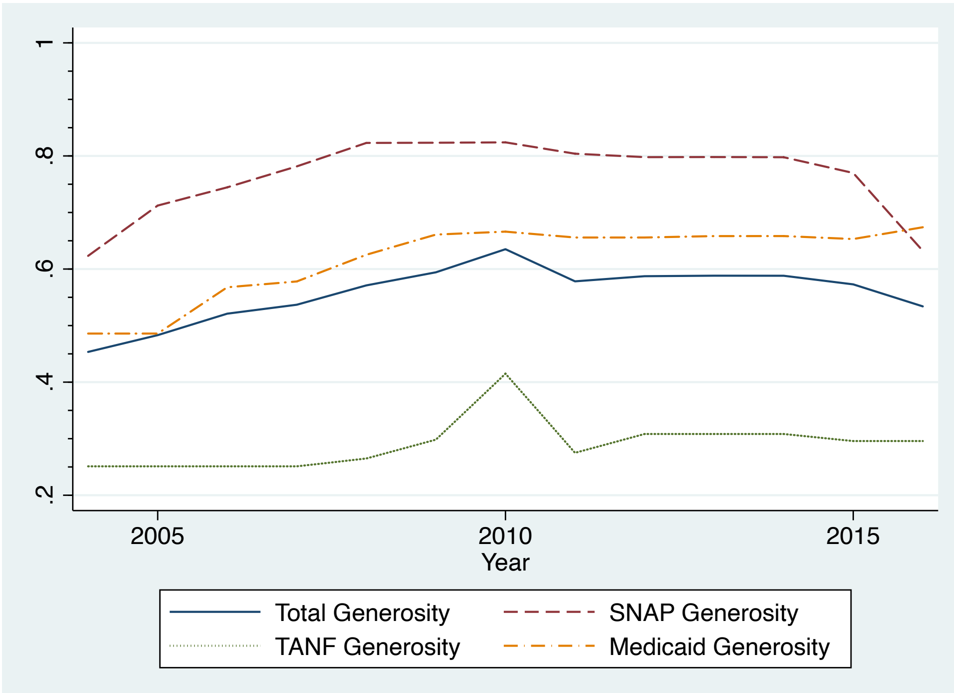
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.49 West Virginia Generosity 2004–2016



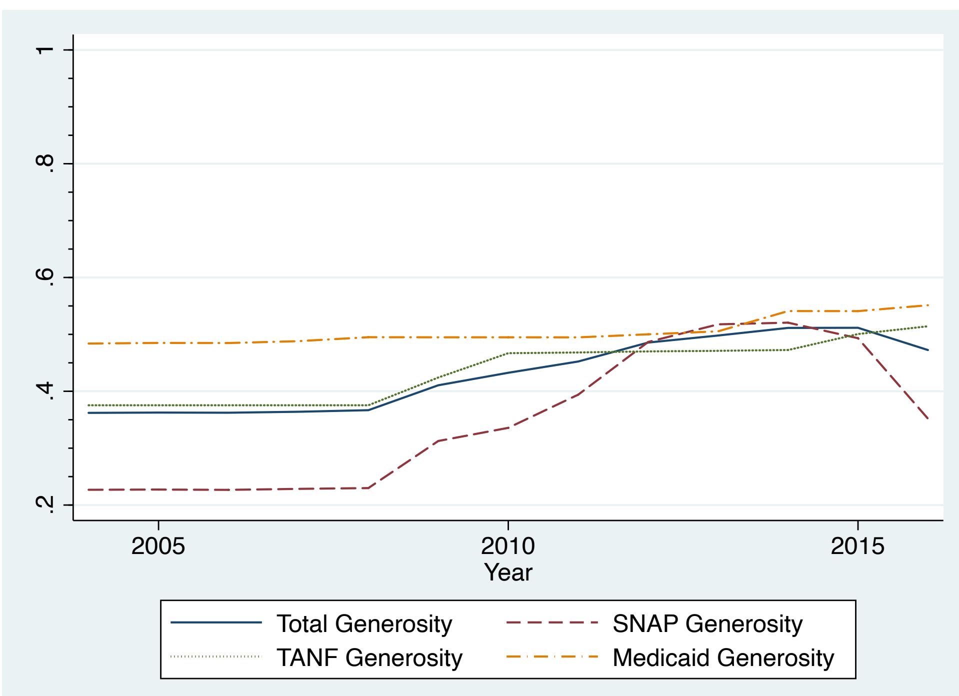
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.50 Wisconsin Generosity 2004–2016



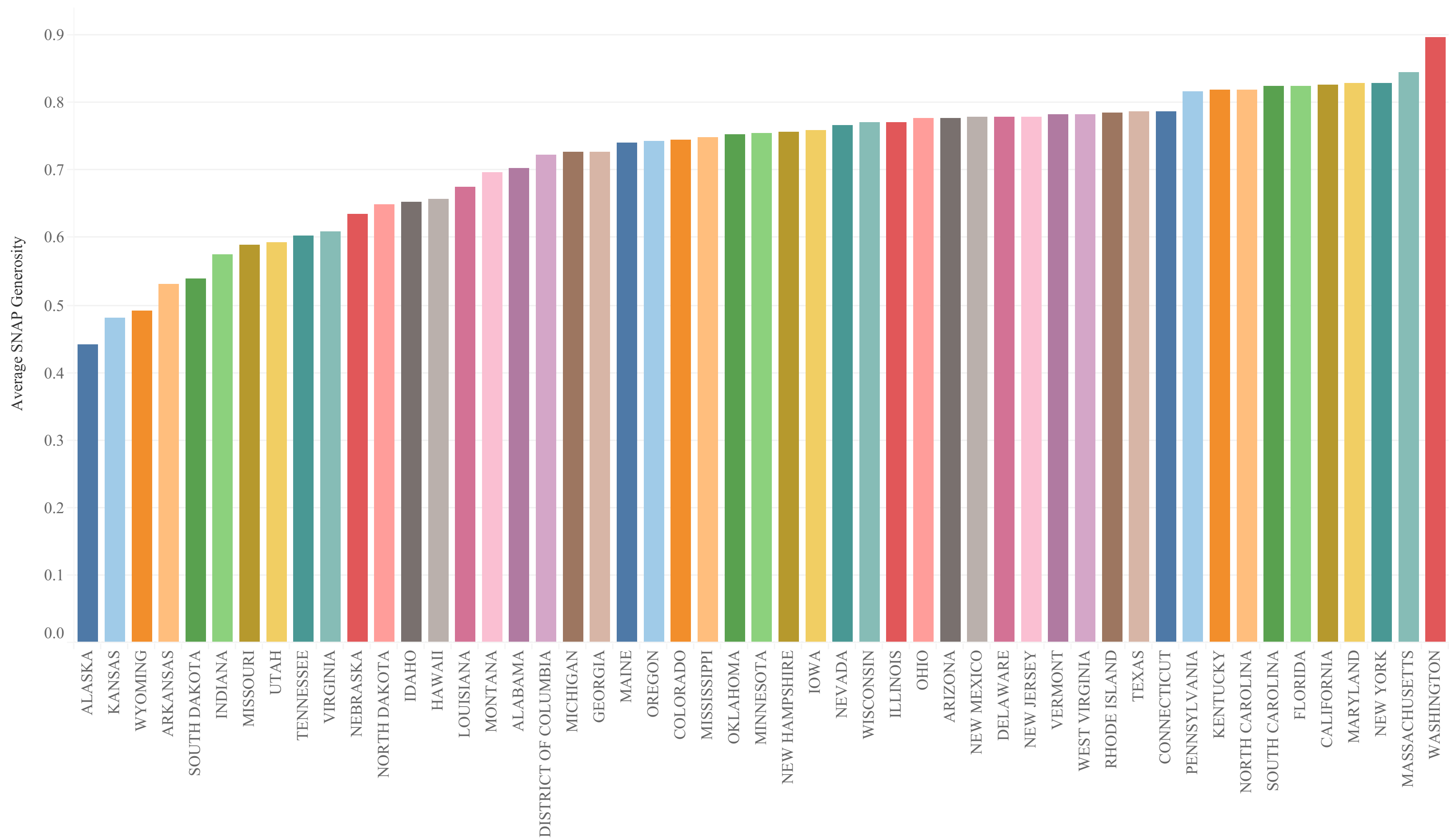
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.51 Wyoming Generosity 2004–2016



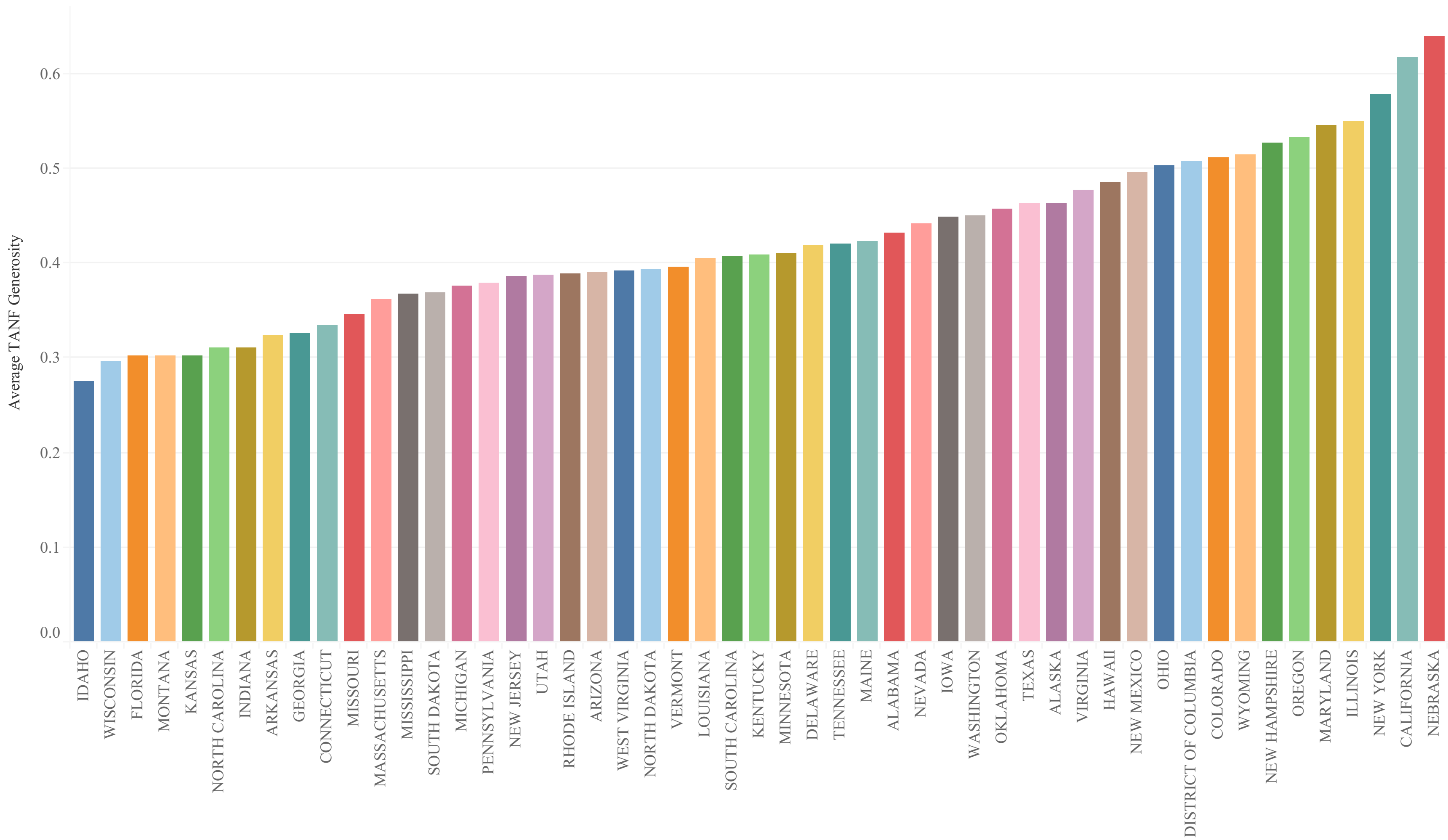
Note. SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.

Figure A.2.52 Average SNAP Generosity Score by State, 2004–2016



Note. SNAP = Supplemental Nutrition Assistance Program.

Figure A.2.53 Average TANF Generosity Score by State, 2004–2016



Note. TANF = Temporary Assistance to Needy Families.

Figure A.2.54 Average Medicaid Generosity Score by State, 2004–2016

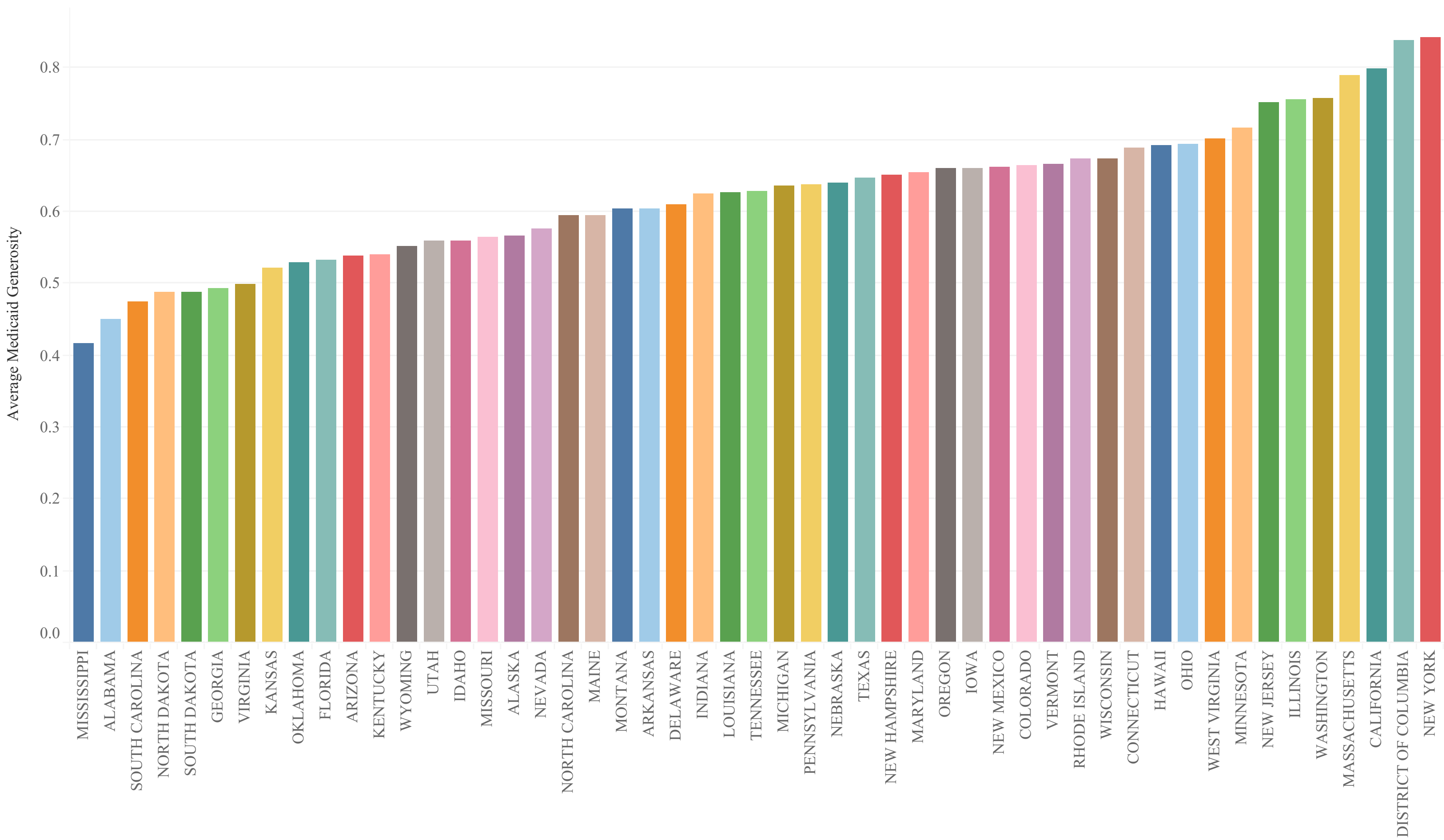
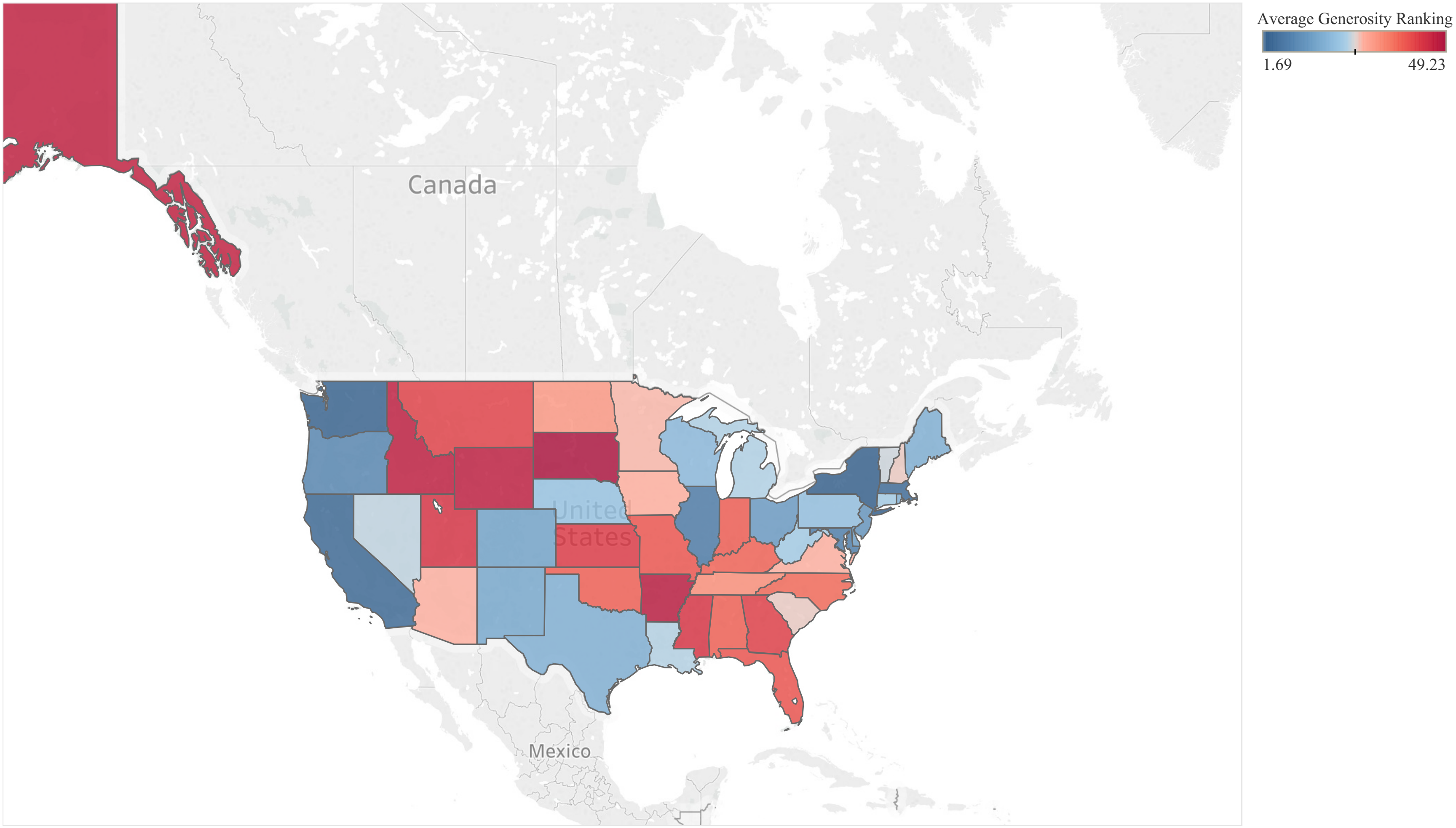


Figure A.2.55 Average Total Generosity Rank



APPENDIX 3: MULTILEVEL MAXIMUM LIKELIHOOD ESTIMATION RESULTS, MMR OF RESIDENTS OF A STATE

Table A.3.1 *Results for Extended Maternal Mortality*

	(1)	(2)	(3)	(4)	(5)
	MMR1	MMR1	MMR1	MMR1	MMR1
Generosity	-0.102				
	(0.112)				
Revised	18.19***	17.91***	18.10***	17.82***	18.05***
	(1.870)	(1.870)	(1.789)	(1.834)	(1.854)
High BMI	1.242***	1.225***	1.224***	1.168***	1.218***
	(0.276)	(0.290)	(0.265)	(0.273)	(0.300)
SNAP		-0.0202			0.00441
		(0.0534)			(0.0576)
TANF			-0.246		-0.250
			(0.128)		(0.133)
Medicaid				-0.0331	0.00466
				(0.112)	(0.118)
_Cons	-11.38	-14.80*	-6.409	-12.64	-6.603
	(7.911)	(6.992)	(8.106)	(10.16)	(10.91)
X^2	137.60***	136.38***	142.34***	136.34***	142.34***
R^2	.30916168	.30337006	.3258253	.30374207	.3256912

Note. $N = 408$. BMI = body mass index; MMR = maternal mortality ratio; SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.3.2 *Results for Limited Maternal Mortality*

	(1)	(2)	(3)	(4)	(5)
	MMR2	MMR2	MMR2	MMR2	MMR2
Generosity	-0.192**				
	(0.0701)				
Revised	10.48***	10.29***	9.801***	9.919***	10.43***
	(1.187)	(1.200)	(1.165)	(1.179)	(1.190)
Black population	29.74***	30.28***	27.43***	28.41***	29.27***
	(5.639)	(5.817)	(5.778)	(5.809)	(5.724)
SNAP		-0.0718*			-0.0538
		(0.0337)			(0.0351)
TANF			-0.139		-0.0962
			(0.0771)		(0.0784)
Medicaid				-0.105	-0.0669
				(0.0628)	(0.0633)
_Cons	16.06***	10.50***	12.35***	12.54***	16.99***
	(3.589)	(2.128)	(3.298)	(3.618)	(4.291)
X^2	95.55***	90.34***	88.61***	87.39***	95.93***
R^2	.27267447	.26301854	.26018157	.25731159	.27333596

Note. $N = 408$. BMI = body mass index; MMR = maternal mortality ratio; SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families.Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.3.3 *Results for Extended White Maternal Mortality*

	(1)	(2)	(3)	(4)	(5)
	White MMR1	White MMR1	White MMR1	White MMR1	White MMR1
Generosity	-0.0404				
	(0.113)				
Revised	17.27***	16.99***	17.42***	17.12***	17.18***
	(1.897)	(1.896)	(1.811)	(1.863)	(1.870)
High BMI	1.044***	1.007***	1.041***	1.019***	0.980**
	(0.271)	(0.286)	(0.261)	(0.274)	(0.298)
SNAP		0.0105			0.0328
		(0.0547)			(0.0588)
TANF			-0.204		0.0328
			(0.125)		(0.0588)
Medicaid				-0.0112	-0.00690
				(0.109)	(0.115)
_Cons	-12.28	-13.87*	-6.370	-13.02	-5.569
	(8.101)	(6.984)	(8.107)	(10.26)	(10.90)
X^2	114.77***	114.32***	119.59***	114.42***	120.04***
R^2	.27703009	.27358113	.29500273	.27481424	.29569936

Note. *N* = 408. BMI = body mass index; MMR = maternal mortality ratio; SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.3.4 *Results for Limited White Maternal Mortality*

	(1)	(2)	(3)	(4)	(5)
	White MMR2	White MMR2	White MMR2	White MMR2	White MMR2
Generosity	-0.249***				
	(0.0712)				
Revised	8.761***	8.437***	8.095***	8.279***	8.691***
	(1.195)	(1.235)	(1.183)	(1.204)	(1.182)
SNAP		-0.0804*			-0.0519
		(0.0354)			(0.0357)
TANF			-0.205**		-0.163*
			(0.0748)		(0.0744)
Medicaid				-0.145*	-0.101
				(0.0606)	(0.0599)
_Cons	20.33***	12.48***	15.95***	15.86***	22.69***
	(3.642)	(2.190)	(3.041)	(3.403)	(4.059)
X^2	57.62***	47.42***	51.90***	49.25***	60.92***
R^2	.16108253	.13751938	.15002453	.14394409	.1675403

Note. $N = 408$. MMR = maternal mortality ratio; SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.3.5 *Results for Extended Black Maternal Mortality*

	(1)	(2)	(3)	(4)	(5)
	Black MMR1	Black MMR1	Black MMR1	Black MMR1	Black MMR1
Generosity	0.288				
	(0.253)				
Revised	23.85***	24.55***	24.92***	24.08***	23.75***
	(4.144)	(4.122)	(4.034)	(4.035)	(4.121)
High BMI	1.506**	1.412*	1.506**	1.893**	1.797**
	(0.561)	(0.594)	(0.570)	(0.623)	(0.681)
SNAP		0.0868			0.0395
		(0.126)			(0.133)
TANF			0.162		0.0580
			(0.282)		(0.289)
Medicaid				0.289	0.255
				(0.221)	(0.239)
_Cons	-22.08	-10.21	-13.79	-33.95	-33.76
	(19.44)	(15.68)	(18.06)	(24.76)	(25.38)
X^2	52.60***	51.23***	50.99***	53.33***	53.57***
R^2	.21561217	.20685718	.20519614	.22030113	.22137025

Note. $N = 254$. BMI = body mass index; MMR = maternal mortality ratio; SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.3.6 *Results for Limited Black Maternal Mortality*

	(1)	(2)	(3)	(4)	(5)
	Black MMR2	Black MMR2	Black MMR2	Black MMR2	Black MMR2
Generosity	0.260				
	(0.209)				
Revised	15.52***	15.99***	16.40***	16.38***	15.53***
	(3.410)	(3.390)	(3.318)	(3.329)	(3.410)
SNAP		0.0951			0.0773
		(0.101)			(0.104)
TANF			0.181		0.119
			(0.228)		(0.235)
Medicaid				0.119	0.0852
				(0.163)	(0.166)
_Cons	12.59	20.04**	18.73*	18.96*	11.98
	(10.72)	(6.372)	(8.884)	(9.339)	(11.79)
X^2	28.28***	27.37***	27.07***	26.98***	28.32***
R^2	.1317627	.12482202	.12365505	.12382123	.13198761

Note. *N* = 254. MMR = maternal mortality ratio; SNAP = Supplemental Nutrition Assistance Program; TANF = Temporary Assistance to Needy Families. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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